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# Restoration of the service and loss minimization in electrical distribution systems

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**ABSTRACT**

Restoration of service during faults to healthy zones and the minimization of true or real power losses are the main aspects of the satisfactory operation of an electrical distribution system (EDS). These objectives can be achieved with artificially intelligent optimisation techniques through electrical distribution system reconfiguration. The restoration of service is an important part of ensuring a stable power supply. If there is a fault with the EDS, the damaged zone is separated, and the healthy system is restored without breaching limitations. In the distribution system, ohmic losses are 25-35%. It is essential to reconfigure the system to reduce these losses. In this paper, a hybrid artificial rabbits' optimisation and improved mayfly optimisation (ARO-IMO) technique is adopted for restoration of service and loss minimization. The method being suggested will be carried out on an IEEE 4-feeder network for restoration of service and on IEEE 33 and 69 radial distribution networks (RDN) for diminution of losses.



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## 1. INTRODUCTION

The most researched and challenging problems are loading balancing and restoring service to distribution lines in emergency situations. To evenly distribute the loads and resume service to healthier sections in the case of a fault, the network is reconfigured. The issue of diminution of power losses and strengthening voltage distribution through reconfiguration was not addressed in this method [1]. The procedure for changing the status of switches is known as reconfiguration, and its aim is to shorten losses and strengthen voltage distribution [2], [3]. The optimisation challenge is solved with a heap-based optimizer that employs a corporate rank hierarchy to obtain the best radial distribution networks (RDN). The target functions of this technique include voltage pattern enhancement, power loss diminution, and cost-of-operation minimization. The suggested method has only been demonstrated on an IEEE 33 RDN [4]. By choosing an appropriate power flow path, restoring service allows the feeder's healthy section to be re-energized [5], [6]. Following the detection and isolation of the faulty component, an automated reconfiguration method is carried out to recover the greatest feasible impacted loads without additional disruptions during repair activities. This approach gets more challenging in networks with integrated distributed generating units, which might pose security issues for the modified network following a failure occurrence. To address these issues, a probabilistic framework is provided. However, the uncertainties in generation are not addressed by this method [7].

For optimised reconfiguration to lower losses and strengthen the voltage pattern, a genetic algorithm (GA) enabled particle swarm optimisation (PSO) was presented. It alters the configuration of an existing network by utilising the diverging characteristics of PSO along with the enhanced impact of GA. The suggested method has only been demonstrated on an IEEE 33 RDN [8]. To diminish power losses during reconfiguration, a modified sequential switch opening and exchange strategy integrating and excluding distributed generations (DG) has been developed. For reconfiguration, the needed search range for each iteration step is altered using this technique. This method was unable to deal with the load uncertainties [9]. Reconfiguration and DG deployment are widely used to shorten the losses in power and boost voltage profiles. The DG's spots and size are the most important indicators of the DG's deployment. The challenge of restoring service to healthy areas by means of reconfiguration following a malfunction is not addressed in these methods [10], [11]. A heuristic network reconfiguration approach built around branch exchange was established. The suggested bus categorization technique dynamically transforms according to the changing topology to deliver a reconfigured network with minimal loss [12]. The moth swarm strategy, a contemporary metaheuristic driven by moths' dark navigating strategy for identifying sources of food, has been created to diminish power losses by means of reconfiguration. This method is not planned for implementation in practical RDN [13]. As a useful technical solution for distribution system operators to increase system efficiency overall, the reconfiguration strategy has evolved. Sectionalizing and tie switches are frequently used to modify the RDN architecture. These switches have a usually closed or usually open setting. The switch states can be modified manually or electrically to reach the ideal configuration with a noticeable increase in voltage levels and reduction of system losses [14]–[17]. A RDN operation optimization using mixed PSO has been offered to shorten losses in power and magnify the voltage in RDN. The challenge of restoring service to healthy areas by means of reconfiguration following a malfunction is not addressed in this method [18]. A distribution network has inadequate voltage control and suffers from significant power losses as compared to a transmission system. One method for minimising distribution system losses is reconfiguration [19], [20]. Increased real losses in power and smaller voltages at buses affect electrical distribution system (EDS). Approaches for reconfiguration and ideal capacitor placement are among the most affordable and effective methods for diminishing loss and enhancing voltage patterns while accomplishing EDS restrictions [21]. To minimise network power loss, a chemical reaction optimisation method was created for optimal reconfiguration of RDN. Up to a certain point, the reconfiguration process can reduce losses in power. It is possible to lessen power loss even further by positioning the capacitor optimally. The task of resuming service to healthy regions through reconfiguration after a fault is not addressed [22].

By combining deep learning with robust optimisation, a generic, robust method for reconfiguration that guards against the danger posed by inconsistencies in current distributive systems was provided. In 3-Φ unbalanced RDN, this approach may be used for both loss reductions and the balance of loads [23]. In an EDS, the DG in the electrical system and the consumer's load requirements are continually changing. Multi-objective optimal network reconfiguration, taking into consideration variations in demands and DG, has therefore become a significant task. To handle the multi-objective optimum issue of reconfiguration, the chaos disturbed beetle antennae search method was developed. The task of resuming service to healthy regions through reconfiguration after a fault is not addressed [24]. To lower losses in power, a new, improved harmony search algorithm was developed to address network reconfiguration issues [25]. Reconfiguration provides several important benefits, such as improved voltage levels, load balance, and decreased losses. Despite being normally constructed with a structure composed of mesh, distribution systems usually function in a radial manner [26].

The selected technique addresses the limitations of most of the methods described in the preceding paragraphs. To overcome the issues of poor convergence rate, limited search capacity, and time-demandingness that are encountered when exploring, exploiting, and conquering nature, several optimization methods have been developed. However, most algorithms still lack the ability to address all the above issues. Artificial rabbits' optimisation (ARO) and improved mayfly optimisation (IMO) are recently developed meta-heuristic algorithms that address the inadequate search capabilities and poor convergence efficiency of the present approaches. Combinatorial optimization issues are particularly well suited for these meta-heuristic algorithms. Problems involving global optimization can be solved with these techniques. Restoration of service and diminution of losses in an EDS could be achieved through reconfiguration. In this study, a hybrid ARO-IMO algorithm is implemented on an IEEE 4-feeder network for restoring service by using the concept of reconfiguration. The adopted methodology is accomplished on IEEE 33 and 69 RDN for diminution of losses. Owing to their ability to find the global optimum (rather than the local optimum) in a very short time, the following goals are achieved in this study using a hybrid (ARO-IMO).

- To achieve the finest results possible, service restoration paths in the IEEE 4-feeder network during faults.
- To get the best-reconfigured network feasible in IEEE 33 and 69 RDN for diminution of losses.
- To enhance the voltage profile in IEEE 33 and 69 RDN.

The following is the investigation's structure: the second section presents the investigation's problem description. The third section defines the suggested method's equations for computation. The fourth section shows the outcome analysis and comparison. The fifth section states the findings of this study.

## 2. PROBLEM FORMULATION

The objectives of this work, restoration of service and diminution of losses could be achieved through reconfiguration. In this study, a hybrid ARO-IMO algorithm is implemented on an IEEE 4-feeder network for restoring service. The adopted methodology is also accomplished on IEEE 33 and 69 RDN for diminution of losses. The suggested method has dual objective functions, represented by (1) and (2).
Minimization of load balancing index given by;

$$LBI = \frac{1}{n}\sqrt{\Sigma(y - y_i)^2} \tag{1}$$

Here n remains the total number of feeders. The average of the normalized loads $y_i$ is y.
Minimization of loss given by;

$$f = \sum_{A=1}^{n} R_A \frac{{P_A}^2 + {Q_A}^2}{|V_A|^2} \tag{2}$$

Where n is number of branches, $R_A$, $P_A$, $Q_A$, $V_A$ are branch resistance, true power, wattless power, and voltage of branch A.
With respect to the confines;

- The system's radial topography must be sustained. Feeders must not be loaded in excess.
- Voltage and current magnitudes are within acceptable ranges.
- $V_{mn} \leq V_A \leq V_{mx}$; $I_{mn} \leq I_A \leq I_{mx}$

where the Ath bus's minimum and maximum voltage limitations are $V_{mn}$ and $V_{mx}$, minimum and maximum current limitations are $I_{mn}$ and $I_{mx}$ respectively.

### 2.1. Algorithm of the adopted method

The desired outcomes of this work, which include restoration of service and reduction of losses, could be met through reconfiguration. Owing to the ability of ARO-IMO to find the global optimum (rather than the local optimum) in a very short time, in this study, a hybrid ARO-IMO technique is used to restore service on an IEEE 4-feeder network. The suggested approach is also carried out on IEEE 33 and 69 RDN for loss reduction. The detailed step-by-step algorithm for the ARO-IMO technique is mentioned Algorithm 1.

Algorithm 1. Step-by-step for the ARO-IMO
```
1.  Take the input data provided by IEEE 33, 69, and 4-feeder network for resistance,
    reactance, bus load, and zone load.
2.  Check the IEEE 4-feeder network for any failures that may have occurred on any of the
    feeders.
3.  If a fault develops on any of the feeders, isolate the faulty section and determine
    what zones are disconnected from service, and then proceed to step 4. If none of the
    feeders have a fault, go to step 12.
4.  Place the population (tie switches), the highest possible number of iterations, and ARO
    variables like
    lower and upper bounds for search space, energy factor, and hiding parameter in their
    initial settings.
5.  Create a population of tie switches at random. The ARO method selects any switch to
    function as a tie switch at random among the switches available for the IEEE 4-feeder
    network.
6.  Proceed with reconfiguration without violating the confines mentioned in the problem
    formulation.
7.  Inspect to determine if the rebuilt system is radial in nature. If true, estimate the
    LBI given by (1). Select the elite with the smallest LBI. If false, proceed through
    step 6.
8.  Determine the rabbit energy E (8). If E>1, perform the exploration phase and update the
    position of tie switches by (3), or else perform the exploitation phase and update the
    position of tie switches by (9).
9.  Upon their positions being modified, assess the fitness LBI of all rabbits (tie
    switches).
10. Substitute the elite with this one if the fitness LBI number is lower.
11. If the greatest possible number of successive iterations has been attained, upgrade the
    elite (the LBI with the smallest value, indicating the best way to restore service).
12. Construct a starting Mayfly (tie switch) population, both male and female. Set the
    highest possible number of iterations.
13. Proceed with reconfiguring the IEEE 33/69 RDN.
14. Inspect to determine if the rebuilt system is radial in nature. If true, estimate the
    losses given by (2) for all tie switches. In each iteration, the Pbest and Gbest are
    obtained. If false, proceed through step 13.
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15. Change the positioning and the velocity of the male and female mayflies (tie switches)
    given by (14) and (15).
16. Evaluate their fitness (losses from (2)) and rank the mayflies.
17. Calculate the velocity of a mayfly via Levi flight. Determine the gravity coefficient
    and estimate the offspring.
18. Divide an offspring at randomly among male and female mayflies. Substitute better
    solutions with inferior ones (lowest loss value).
19. Pbest and Gbest should be updated.
20. When the permitted number of iterations has been achieved, print the optimum solution
    with lowest loss.
```

## 3. PROPOSED METHOD

The major aim of the adopted methodology is to restore service to healthy zones during faults and mitigate losses. These objectives can be achieved by reconfiguring the EDS. The ARO technique is used to identify the optimal service restoration path during faults in an IEEE 4-feeder network, and the IMO technique is applied for loss minimization in IEEE 33 and 69 RDN. The ARO technique uses the load balancing index given by (1) to identify the restoration path. The IMO technique aims at loss minimization, as given by (2).

### 3.1. Artificial rabbits' optimization

In this study, ARO is used to identify the best approach for service restoration. When a feeder experiences a breakdown, the breaker trips, isolating the affected region. Discover which active zones are unavailable (fault-affected zones). Calculate LBI and reconfigure the system while sticking to the limits. The configuration that yields the lowest LBI value while fulfilling all other requirements is the optimal configuration for restoring service. The following stages demonstrate how the ARO [27] technique searches:

#### 3.1.1. Detour foraging (exploration)

When foraging, the rabbit makes the decision to randomly move to far-off places in quest of food, unaware of what is nearby. A rabbit does not eat grass near its own nest. This is called detour foraging, and (3) to (7) demonstrate its numerical equation;

$$X_i(t+1) = X_j(t) + A \times (X_i(t) - X_j(t) + round(0.5 \times R_1)) \times n_1 \quad (3)$$

$$A = L \times b \quad (4)$$

$$L = \left(e - e^{\left(\frac{t-1}{T}\right)^2}\right) \times sin\,(2\pi R_2) \quad (5)$$

$$g = randperm\,(D) \quad (6)$$

$$n_1 \sim N(0,1) \quad (7)$$

where:

$X_i(t+1) \rightarrow Candidate\ position\ of\ the\ i^{th}\ rabbit\ in\ iteration$ t+1

$X_i(t) \rightarrow Position\ of\ i^{th}\ rabbit\ in\ iteration\ t$; $X_j(t) \rightarrow Position\ of\ j^{th}\ rabbit\ in\ iteration\ t$

$b(k) = \begin{cases} 1, & if\ k == g(l) \\ 0, & otherwise \end{cases} \quad k = 1, \ldots, D\ and\ l = 1, \ldots, [R3 \times D]$

$L \rightarrow running\ length\ of\ the\ rabbits$; $N \rightarrow Denotes\ the\ population\ size$

$T \rightarrow Maximum\ number\ of\ iterations$; $D \rightarrow Dimension\ size$

Randperm (D) is an arbitrary integer between 1 and D;

$R_1$, $R_2$, $R_3$, and $R_4$ are all arbitrary numbers in the range [0, 1].

#### 3.1.2. Transition from exploration to exploitation

It has already begun to transition away from exploration, and it will do so over time. The rabbit energy E is given by (8). In ARO, rabbits commonly engage in random concealment in the later stages of the hunt if E≤1, whereas they are more likely to engage in continuous detour foraging in the first phases of the iteration if E>1.

$$E(t) = 4\left(1 - \frac{t}{T}\right) In\ \frac{1}{R_4} \quad (8)$$

### 3.1.3. Random hiding (exploitation)

Predators frequently chase after and harm rabbits. To survive, they were going to dig various kinds of shelter-filled burrows close to the nest. A rabbit always constructs D tunnels throughout the dimensions of the searching area before selecting one at random to hide in. The mathematical explanation of this tendency is shown in (9) to (13);

$$X_i(t+1) = X_i(t) + A \times (R_5 \times b_{i,r}(t) - X_i(t)) \tag{9}$$

$$b_{i,r}(t) = X_i(t) + H \times g_r(k) \times X_i(t) \tag{10}$$

$$g_r(k) = \begin{cases} 1, & if\ k == [R_6 \times D] \\ 0, & otherwise \end{cases} \tag{11}$$

$$H = \frac{T-t+1}{T} \times n_2 \tag{12}$$

$$n_2 \sim N(0,1) \tag{13}$$

$b_{i,r}(t)$ depicts the i$^{th}$ rabbit's burrow at random from D burrows. In the present version, burrows are utilised for hiding, $R_5$ and $R_6$ are two random numbers between 0 and 1, and $n_2$ follows the standard normal distribution.

## 3.2. Improved mayfly optimization

The improved mayfly optimization technique is used to find optimal reconfiguration to mitigate losses. After creating a population at random (tie switches), the system is reconfigured. The adopted method gives only feasible configurations that obey the limits and discards all other configurations. The losses are calculated for each reconfigured network, the optimal option is the one with the smallest losses. Using the same parameters as the optimisation algorithms and velocity, the MO approach moves the male mayflies (tie switches) in accordance with their current locations. Using (14), each of these mayflies should adjust their locations.

$$p_i(t+1) = p_i(t) + v_i(t+1) \tag{14}$$

### 3.2.1. Movements of mayflies

The velocity has altered because of changes in actual fitness $f(x_i)$ and peak fitness $f(x_{h_i})$ in prior movements. I$f$ $f(x_i) > f(x_{h_i})$, the previous best movements are listed in (15);

$$v_i(t+1) = g.v_i(t) + \alpha_1 e^{-\beta \gamma_p^2}\left[x_{h_i} - x_i(t)\right] + \alpha_2 e^{-\beta \gamma_g^2}\left[x_g - x_i(t)\right] \tag{15}$$

$g$ is listed as variable; but $\alpha_1, \alpha_2\ and\ \beta$ are considered stable. The terms $\gamma_p\ and\ \gamma_g$ which are stated in (16) relate to the cartesian spacing.

$$\|x_i - x_j\| = \sqrt{\sum_{k=1}^{n}(x_{ik} - x_{jk})^2} \tag{16}$$

$If\ f(x_i) < f(x_{h_i})$. Based on the unconventional dance component d outlined in (17), male mayflies alter their velocity depending on their actual status.

$$v_i(t+1) = g.v_i(t) + d.\gamma_1 \tag{17}$$

this value $\gamma_1$ is designated as indiscriminate.

### 3.2.2. Female mayflies' motion

Female mayflies were able to change their movements noticeably to contact male mayflies to breed. Female mayflies have a lifetime of one to seven days and are wingless. Therefore, depending on which male mayflies they intended to catch, they could change their speed. According to the MO technique, in the physically fittest mayflies, both sexes had to procreate first; in subsequent generations of mayflies and both sexes may have procreated quickly. Therefore $if\ f(y_i) < f(x_i)$, in (18) is written as,

$$v_i(t+1) = g.v_i(t) + \alpha_3 e^{-\beta\gamma_{mf}^2}[x_i(t) - y_i(t)] \tag{18}$$

as a substitute, the value of $\alpha_3$ has been provided, and the value of $\gamma_m$ represents cartesian distance. $If\ f(y_i) < f(x_i)$, Female mayflies change their motions if the current one goes through extra dance factors. Therefore, $fl$ is written as (19);

$$v_i(t) = g.v_i(t) + fl.\gamma_2 \tag{19}$$

the indiscriminate values are marked by the symbol $\gamma_2$.

### 3.2.3. Mating of mayflies

The upper half of the mayflies could couple up and have two or more children. The (20) and (21) suggest that the parents' offspring may appear at any time;

$$\text{first offspring} = (1 - \text{L}) \times \text{female} + \text{L} \times \text{male} \tag{20}$$

$$\text{Second offspring} = (1 - \text{L}) \times \text{male} + \text{L} \times \text{female} \tag{21}$$

gaussian distribution is used to represent L.

### 3.2.4. Improved mayfly

In (17) and (19) demonstrate that under specific circumstances, a group's members will alter the swarm's speed at random. In other situations, efficient systems can be employed to change the speed. In (15) and (18) change velocity using current balance velocity and weighted length, ranging from the best overall option, previous best movement, or spouses. In (22) shows how the corrected distance component appears in more contexts.

$$v_p = \alpha_i e^{-\beta\gamma_j^2}(p_j - p_i) \tag{22}$$

to consider such a scenario, change (22) as (23).

$$v_p = \alpha_i e^{-\frac{\beta}{\gamma_j}}(p_j - p_i) \tag{23}$$

## 4. RESULTS AND DISCUSSION

The research was performed using MATLAB 2021b and Windows operating systems running at 2.7 GHz with an i7-7500UCPU and 16 GB of RAM. The suggested ARO-IMO technique is used to identify the optimal service restoration path during faults in an IEEE 4-feeder network and for loss minimization in IEEE 33 and 69 buses. The restoration path is identified using the ARO approach using the load balancing index provided by (1). Loss reduction is the goal of the IMO approach, as indicated by (2).

### 4.1. Restoration of service in IEEE 4-feeder network

Figure 1 displays the IEEE 4-feeder network basic setup, which is employed in the evaluation of the suggested ARO-IMO approach. The switches S1 to S20 are sectionalizing switches, and switches T1 to T15 are tie switches. Each loading feeder has a 10 MVA capacity. The loads on feeders F1, F2, F3, and F4 are 6,500, 4,300, 8,800, and 7,300 kVA, respectively. Assume certain random failure developed on feeder F3 at zone Z13 to demonstrate the suggested approach. Due to the fault, switches S13 and S14 are opened to separate the defective area as illustrated in Figure 2. Prior to reconfiguration, the loads on feeders F1, F2, F3, and F4 were 6,500, 4,300, 6,500, and 7,300 kVA, respectively. The LBI for all viable solutions is computed, and the adopted method delivers the restoration path with the lowest LBI. Following reconfiguration, switches T9 and T15 are in a closed state (tie switches), but switch S20 is in an open state (a sectionalizing switch). The optimal restoration path is shown in green in Figure 2. This configuration has the lowest LBI value of 0.0068 out of all feasible configurations. The load on feeder F1 is 6,500 kVA, 6,400 kVA on feeder F2, 6,500 kVA on feeder F3, and 6,800 kVA on feeder F4. The adopted method and the currently used methods for restoring service to healthy zones during a fault in zone 13 are compared in Table 1. The approach chosen outperforms the alternatives that are available in terms of a lower LBI, which indicates the best configuration.

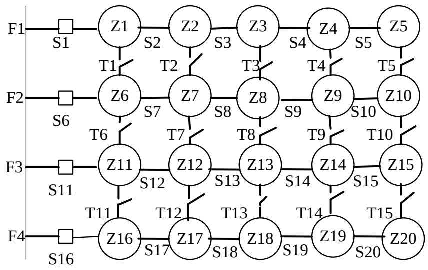


Figure 1. IEEE 4-feeder base configuration

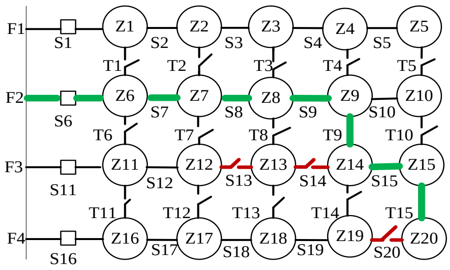


Figure 2. Restoration path after reconfiguration

Table 1. LBI values for restoration of service (fault at zone 13)

| Method | LBI value |
|---|---|
| ALO-IMO [1] | 0.007 |
| AACO [14] | 0.0481 |
| ACO [15] | 0.048 |
| Adopted method | 0.0068 |

## 4.2. IEEE 33-BUS RDN

Figure 3 displays the IEEE 33 RDN basic setup, which is employed in the evaluation of the suggested ARO-IMO approach. The switches 1 to 32 are sectionalizing switches, and switches 33 to 37 are tie switches. The IMO technique is used to find optimal reconfiguration to mitigate losses. After creating a population at random (tie switches), the system is reconfigured. The adopted method gives only feasible configurations that obey the limits and discards all other configurations. The losses are calculated for each reconfigured network, the optimal option is the one with the smallest losses, as shown in Figure 4.

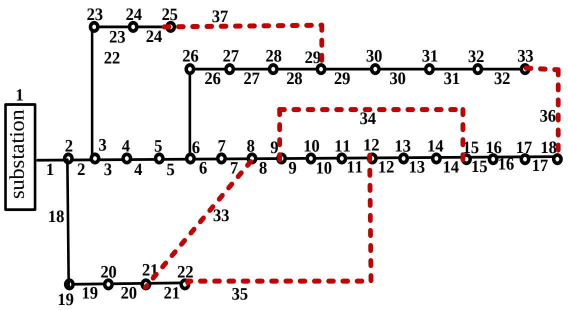


Figure 3. IEEE 33 RDN base configuration

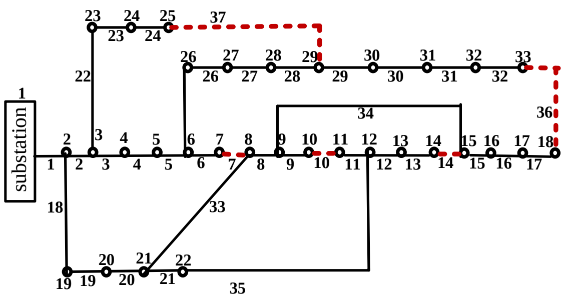


Figure 4. IEEE 33 RDN after reconfiguration

Table 2 shows that the optimal reconfigured network achieved by the adopted methodology is the operation of the tie-switches 7, 10, 14, 36, and 37. This optimal configuration has the lowest losses at 95.83 kW when compared with the other feasible configurations. The adopted methodology has lowered real power losses on the IEEE 33 RDN to 95.83 kW from 202.69 kW for the IEEE 33 RDN base configuration. The proposed method also improved the per-unit voltage magnitude to 0.9542 as compared with existing methods.

Table 2. Outcomes for IEEE 33 RDN

| Parameter | Base configuration | HBO [4] | MSSOE [9] | MSO [13] | Adopted methodology |
|---|---|---|---|---|---|
| Tie-switches | 33, 34, 35, 36, 37 | 7,9,14,32,37 | 7,9,14,32,37 | 7,9,14,28,32 | 7,10,14, 36,37 |
| Real power loss (kW) | 202.69 | 138.01 | 139.55 | 139.98 | 92.83 |
| Loss mitigation | NA | 31.9% | 31.15% | 30.94% | 52.72% |
| Minimal voltage (p.u.) | 0.9107 | 0.94234 | 0.9378 | 0.9412 | 0.9542 |

Real power loss and the minimal possible voltage for IEEE 33 RDN are compared in Figures 5 and 6. Figure 5 shows that the reconfiguration using the adopted methodology resulted in the lowest losses in comparison to the one using the current methods. Figure 6 shows that, compared to the other available approaches, the selected method has provided a superior minimum per unit voltage. Figure 7 shows the results for prior and following reconfiguration node voltages for an IEEE 33 RDN. The Figure 7 showcases that, the voltage levels at all the nodes are improved by implementing reconfiguration through ARO-IMO method.

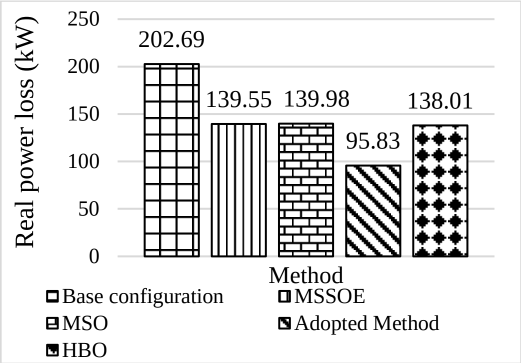


Figure 5. Real power loss comparison (33 RDN)

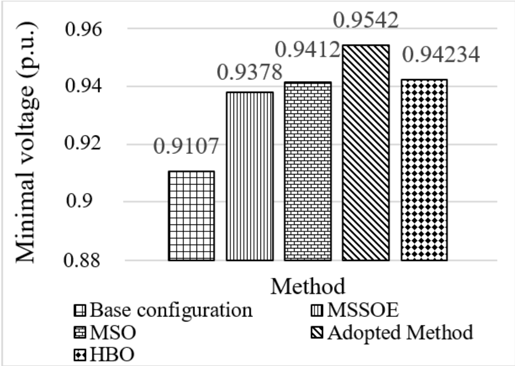


Figure 6. Minimum voltage comparison (33 RDN)

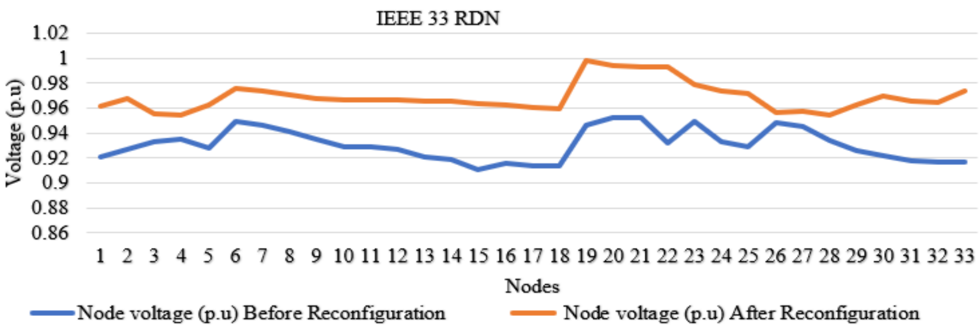


Figure 7. Node voltages prior and post reconfiguration

### 4.3. IEEE 69 RDN

The IEEE 69 RDN shown in Figure 8 is given consideration to evaluate the efficacy of the adopted methodology. It has 68 sectionalizing and 5 tie line switches. It has a 225-kW initial power loss. The IMO technique is adopted to find optimal configuration to mitigate losses. After creating a population at random (tie switches), the system is reconfigured. The adopted method gives only feasible configurations that obey the limits and discards all other configurations. Each reconfigured network's losses are measured, and the one with the fewest losses is deemed to be the optimal option as depicted in Figure 9.

Table 3 exhibits that the optimal reconfigured network achieved by the adopted methodology is the operation of the tie-switches 14, 70, 69, 58, and 61. This optimal configuration has the lowest losses at 34.42 kW when compared with the other feasible configurations. The adopted methodology has lowered real power losses on the IEEE 69 RDN to 34.42 kW from 224.95 kW for the IEEE 69 RDN base configuration. The proposed method also improved the per-unit voltage magnitude to 0.9832 as compared with existing methods.

Table 3. Outcomes for IEEE 69 RDN

| Parameter | Base configuration | ISOS [2] | SOS [2] | MSSOE [9] | Adopted methodology |
|---|---|---|---|---|---|
| Tie-switches | 69,70,71,72,73 | 69,70,14,55,61 | 69,70,13,55,63 | 13,57,61,69,70 | 14, 70,69, 58, 61 |
| Real power loss (kW) | 224.95 | 35.3549 | 36.3982 | 99.69 | 34.42 |
| Loss mitigation (%) | NA | 84.2861 | 83.8224 | 55.68 | 84.6 |
| Minimal voltage (p.u.) | 0.9092 | 0.9806 | 0.9803 | 0.9428 | 0.9832 |

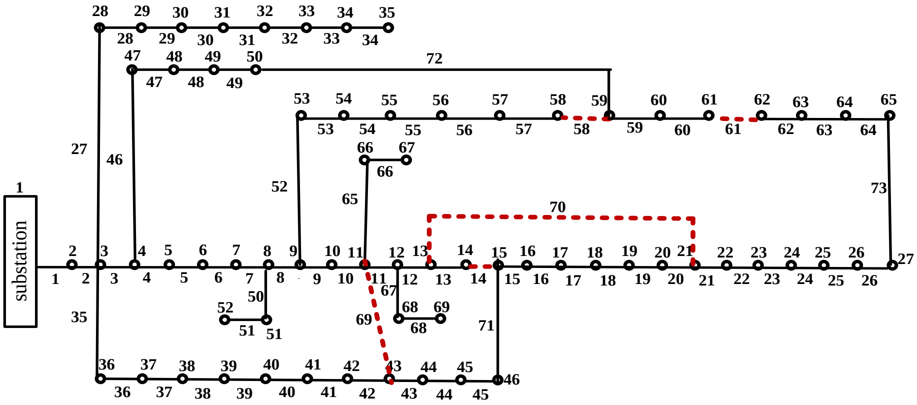


Figure 8. IEEE 69 RDN base configuration

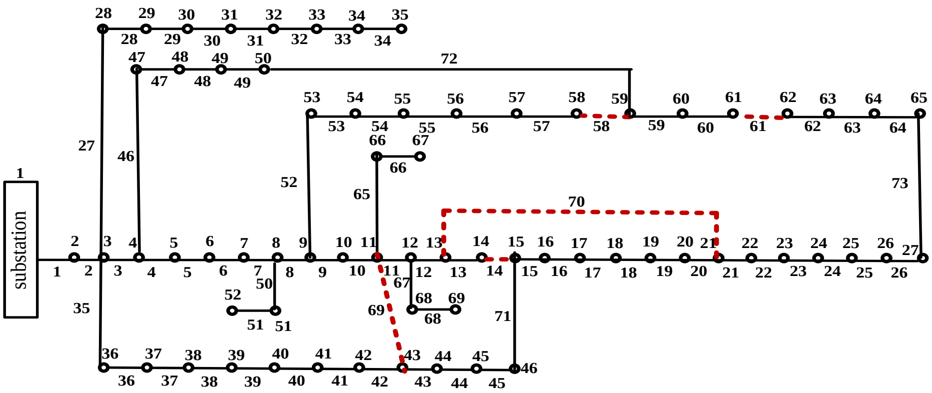


Figure 9. IEEE 69 RDN post reconfiguration

Real power loss and the minimal possible voltage for IEEE 69 RDN are compared in Figures 10 and 11. Figure 10 exhibits that the reconfiguration of the IEEE 69 RDN using the adopted methodology resulted in the lowest losses in comparison to the one using the current methods. Figure 11 shows that, compared to the other available approaches, the selected method has provided a superior minimum per unit voltage. Figure 12 shows the results for prior and following reconfiguration node voltages for an IEEE 69 RDN. Figure 12 showcases that, the voltage levels at all the nodes are improved by implementing reconfiguration through ARO-IMO method.

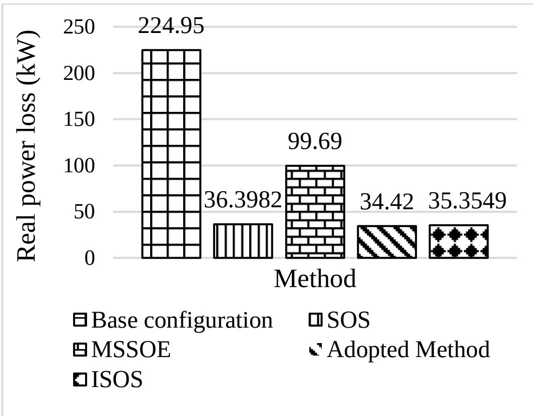


Figure 10. Real power loss comparison (69 RDN)

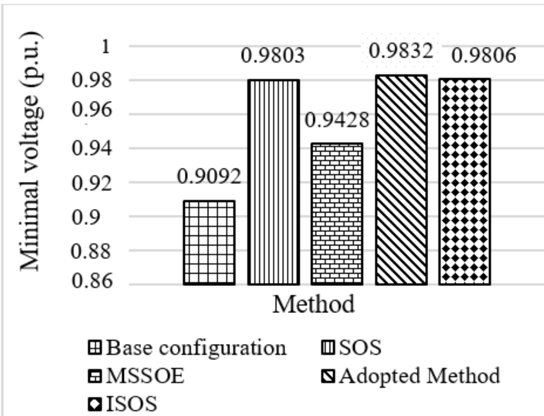


Figure 11. Minimum voltage comparison (69 RDN)

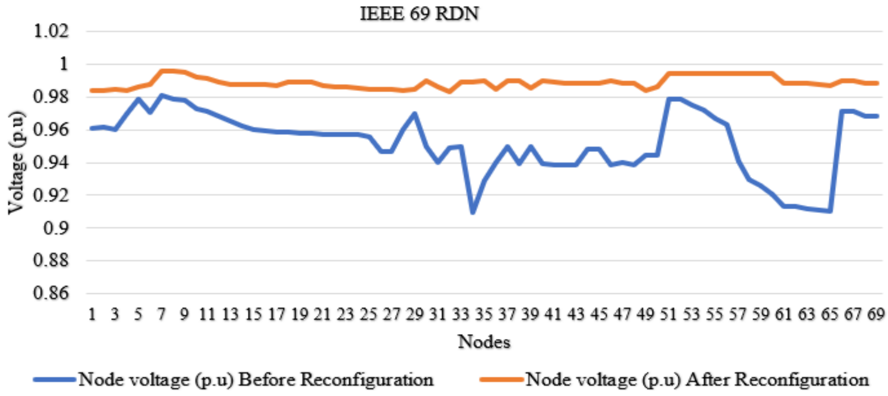


Figure 12. Node voltages prior and post reconfiguration

## 5. CONCLUSION

To restore service for healthy zones during faults and to reduce losses while increasing voltage in RDN, an innovative approach ARO-IMO is introduced in this work. The optimal restoration path for healthy zones is achieved by applying ARO. To minimise the losses in RDN, IMO is suggested to solve the reconfiguration issue and yield the ideal switching combination. The efficacy of the adopted methodology was tested on IEEE 4-feeder network for service restoration and IEEE 33 and 69 RDN for loss minimization. The adopted methodology has shown better results in terms of an optimal service restoration path, lowered loss, and a broadened voltage profile. By examining the reconfiguration under various hybrid algorithms and network topologies, this work will eventually be expanded.

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