Load Balancing and Restoring Service Using Hybrid Ant Lion and Improved Mayfly Optimization Technique

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Abstract

The most common problems encountered in any electrical distribution system are load unbalance and restoring service to healthy zones in the case of a fault. The load on the distribution network is not constant and varies from feeder to feeder throughout the day. In the event of a fault, network reconfiguration is performed to balance the loads and restore service to healthy zones. Network reconfiguration involves modifying the structure of a network by sectionalizing and tie switches. Through reconfiguration, loads can be transferred from a feeder that is relatively heavily loaded to one that is relatively lightly loaded. A hybrid Ant Lion Optimization and Improved Mayfly Optimization (ALO-IMO) technique for load balancing and restoring service is implemented in this paper. The proposed technique is employed for load balancing and restoring service on the IEEE 3 feeder system, as well as restoring service on the IEEE 4 feeder system.

Keywords: ant lion optimization, improved mayfly optimization, load balance, reconfiguration, restoring service

1. Introduction

One of the most researched and difficult challenges is restoring service to distribution networks in emergency scenarios [1]. When a fault isolation procedure occurs, all loads downstream of the faulty site are rendered inoperable [2]. One of the most essential features of smart distribution networks is their ability to self-heal [3]. Restoring service allows the healthy segment of the feeder to be re-energized by determining the best channel for power flow [4]. The tie switches are frequently open, while the sectionalizing switches are frequently closed. To avoid overload problems, the load in an electrical distribution system must be balanced [5, 6]. Network reconfiguration of distribution systems is the solution for loss minimization, load balancing, and restoring service [7, 8]. Overloading causes the voltage in the system to drop, putting more

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Received: 25 Feb 2023 Accepted: 14 March 2023 Published: 1 April 2023
Journal of Asian Energy Studies (2023), Vol 7, 62-76, doi:10.24112/jaes.070005

strain on the feeder than the feeder's design capacity allows [9,10]. Finally, an overloaded feeder or an overcurrent-carrying conductor may cause damage to the conductor. Service restoration is an important component of dependability; however, this is only considered in exceptional circumstances [11,12]. Even though this does not guarantee a 100% power supply, it may provide a better continuous power supply. The apparent power loss is calculated by adding real and reactive power losses [13]. Reactive power is used to keep the system's voltage profile stable and acceptable, whereas real power is required to function effectively and efficiently. As real power loss increases, overall efficiency decreases. Increased system voltage caused by increased reactive power loss causes conductor insulation to fail, resulting in dead short circuits and overall system failure [14,15].

Improvements in load balancing, restoration of the service, and reduction of apparent power loss (i.e., the consistency and continuity of power supply to loads) provide better investment use and enhanced service quality [16]. When compared to a transmission system, a distribution network suffers from considerable power losses and poor voltage control. Reconfiguration is one strategy for reducing losses in the distribution system [17,18].

Although distribution systems are typically built with a mesh structure, they are usually operated in a radial arrangement [19,20]. Tie and sectionalizing switches are the two most common types of switches in a distribution network [21]. The distribution system's operational efficiency can be increased by modifying the functional links between switches or branches [22]. Reconfiguration has several significant advantages, including service restoration, improved voltage levels, load balancing, and reduced losses [23]. Because there are numerous switching combinations that can be used, choosing the best nonlinear combinatorial optimization problem involves switching configuration for a power distribution network issue [24].

A hybrid ALO-IMO algorithm is implemented in this work (1) to obtain the best possible network reconfiguration in IEEE 3 and IEEE 4 feeder systems; (2) to achieve load balance in IEEE 3 and 4 feeder systems; and (3) to restore service to healthy zones in IEEE 3 and 4 feeder systems during faults.

The following is the structure of this research: Section 2 is a review of existing works' literature; Section 3 is the formulation of this research's problem. Section 4 elaborates on the proposed methodology's process; Section 5 analyses and discusses the results. Section 6 discusses the conclusion and the future scope of the work.

2. Literature Review

Juan Wen et al. [1] developed a restoration technique to maximize out-of-service load restoration and use renewable distributed generation while minimizing the number of switch operations. In this study, the distribution system has adequate remotely operated switches to increase restoration performance in terms of time for restoration and magnitude of loads restored. However, the research does not consider load and renewable distributed generation uncertainties.

Mulusew Ayalew et al. [2] suggested a service restoration problem for radial distribution networks that considers protective constraints. The findings highlight the need to address protection restrictions during SR to prevent network protective devices from malfunctioning. The derived service restoration path was not practicable for service restoration without considering security concerns since several protective devices failed to function effectively under typical loading circumstances, and the restored network coordination criteria were not met.

A stochastic framework was presented by Seyed-Alireza Ahmadi et al. [3]. The reconfiguration technique is carried out in this framework using a rapid and reliable mechanism based on graph theory. A chance-constrained programming-based technique is used to address the distribution system's vulnerability to load demand uncertainties. This strategy, however, does not account for generation uncertainties.

Srivastava et al. [5] have demonstrated a hybrid algorithm for restoring service in distribution systems. A machine learning-based system selects the ideal SR scheme from among those produced by several meta-heuristic algorithms for a given fault scenario. The objective value for the supervised ML model was the output of the best meta-heuristic technique, and the input values for the model were the fault characteristics. The method that provides the highest fitness value for service restoration is stored in the database as the fault point's goal value. The fault characteristics produced using the discrete wavelet transform are stored in the database as input labels for the same fault site.

AMPL was utilized by Mahdavi et al. [6] to create a mathematical model for reconfiguration. The model's solvers are commercially accessible. In the study, the suggested model is applied to several test systems and real distribution networks, demonstrating its great efficiency and usefulness for distribution system reconfiguration. Unlike previously evaluated approaches in specialized networks, the suggested formulation is efficient and successful for reconfiguring all sorts of distribution systems with various sizes, buses, and numerous transfer nodes. It necessitates short computation times while avoiding approximations, linearization, decompositions, and complexities.

G. Poornachandra Rao and P. Ravi Babu [7] presented a hybrid Binary Particle Swarm - Ant Lion Optimization technique for reducing losses and enhancing voltage profile through network reconfiguration. The technique was implemented on IEEE 33 bus system. Nevertheless, this approach does not address the lowering of reactive and apparent power losses.

P. Ravi Babu and Molughu Srivani [9] demonstrated Artificial Ant Colony Optimization (AACO) for distribution network reconfiguration for balancing loads and restoring service. This technique solves nonlinear problems while saving time and producing accurate outcomes. This method has a connection to EDS because ant movement is correlated with current, power flow is correlated with pheromone intensity, and line length corresponds to resistance or time consumption. Three goals have been met: the first is load balancing, the second is restoring service, and the third is apparent power loss minimization. Power flow in the system is evaluated using the Direct Load Flow Method (DLFM). DLFM achieves a flat voltage profile, which reduces losses, making it robust, efficient, and suitable for fast convergence.

Jie Wang et al. [20] presented a Chaos Disturbed Beetle Antennae Search Algorithm for Network Reconfiguration with variable loads and DG sizes. Grey target decision-making technique is utilized to rank the beetles for solving the problem in this algorithm. In order to increase the system's static voltage stability and voltage quality, a grey target decision-making model is also built. IEEE 33, 69, and the 118-bus system is used to check the viability and efficacy of the proposed technique.

Ying Wang et al. [21] presented Radial Constraints for Restoring Service and Network Reconfiguration. Additionally, the single-commodity flow constraints, a powerful set of constraints, have been developed in response to research into the spanning tree constraints' drawbacks. A set of mixed constraints was also proposed, and examples demonstrate how the mixed constraints might increase the reconfiguration problem's computing effectiveness. Evaluation and comparison of the sets of effective radiality constraints were done. The test findings have led to recommendations for choosing suitable restrictions for reconfiguration and restoration issues.

3. Problem Formulation

3.1. Load balancing index

Prior to reconfiguring the network, which feeders are overloaded, the capacities of surrounding feeders, and the distributed load are all determined. If any feeder remains overloaded after reconfiguration, perform a load shutdown; otherwise, calculate the load balancing index while keeping the restrictions in mind. A low LBI indicates that the system is keeping a good load balance (i.e., if the LBI is zero, the system's load balance is 100%).

3.2. Objective function

Minimization of load balancing index given by:

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

Where n is the number of feeders and y is the mean of the normalised loadings y_i. Subject to the following constraints:

- The network's radial topology should be retained.
- No feeder should be overloaded.
- Voltage magnitudes are within limits.
- $V_(mn) \leq V_i \leq V_(mx)$

where $V_(mn)$ and $V_(mx)$ are the minimum and maximum voltage limits of ith bus

3.3. Restoring service

As soon as a failure is discovered in a zone or feeder, the circuit breaker trips, separating the area from the problem by turning on the boundary line switches. Determine which fault-affected zones are inaccessible (healthy zones). While adhering to the constraints, perform system reconfiguration and LBI computation. It is critical to keep the load balanced and the important factors within allowable bounds during any reconfiguration. Then, under the stated constraints in Section 3.2, the service restoration of unfaulty zones that are out of service will be carried out one at a time. The best configuration for both load balancing and service restoration is the one that produces the lowest LBI value while meeting all critical criteria.

4. Proposed Method

Natural laws govern biological evolution, and stochastic search and optimization methods called evolutionary algorithms are founded on these ideas. Everyone in the population will compete for the opportunity so that the subsequent generation might inherit their Genetic sequence. The disadvantages of evolutionary algorithms include early convergence and sensitivity to operator parameter selection. ALO-IMO is suggested as a remedy for these limitations. By modifying the network's switching state, ALO-IMO is employed in this study to solve a tough nonlinear, non-differentiable combinatorial optimization problem. Each feeder searches with the expectation of load balancing under the conditions of maximum restoration, resulting in the accurate formation of a restoration plan. Single-objective comparison, unambiguous direction, and low processing complexity are further benefits of this innovative approach.

In the event of a feeder defect, the faulty component is first identified and isolated, and then the upstream portions are separated by turning off the circuit breaker (CB). The downstream components that were not affected are restored by closing the open tie switch with the other sound streams. Then, all line switches connecting to the out-of-service locations without defects are opened to give the greatest number of possibilities for service restoration throughout the decision-making process for restoring service. They are then turned off in accordance with the permitted operating procedures, subject to limitations imposed by the radial arrangement and the current rating of the main transformers and distribution feeders.

4.1. Ant lion optimization

Seyedali Mirjalili [25] presents Ant Lion Optimization. The ALO algorithm involves moving ants randomly, setting up traps, capturing prayers, and setting up new traps. The ALO approach is used to find optimal reconfiguration if any of the feeders become overloaded. A population of ants and antlions (tie switches) is chosen at random. The distribution system is reconfigured, and only networks that are radial and adhere to the constraints are considered. For each reconfigured network, a load-balancing index is computed. The optimal configuration is most likely the one with the lowest LBI value.

The matrix stores the ants' positions at random, as shown in Eq. (2):

$$M_{ant} = \begin{bmatrix} Ant_{1,1} & Ant_{1,2} & \cdots & Ant_{1,d} \\ Ant_{2,1} & Ant_{2,2} & \cdots & Ant_{2,d} \\ \vdots & \vdots & \cdots & \vdots \\ Ant_{n,1} & Ant_{n,2} & \cdots & Ant_{n,d} \end{bmatrix} \tag{2}$$

In this case, $Ant_{i,j}$ depicts the jth value of the ith variable ant, n stands for the number of ants in the population, and d represents the total number of variables. Ant's fitness is shown in Eq (3):

$$M_{OA} = \begin{bmatrix} f[Ant_{1,1} & Ant_{1,2} & \cdots & Ant_{1,d}] \\ f[Ant_{2,1} & Ant_{2,2} & \cdots & Ant_{2,d}] \\ \vdots & \vdots & \cdots & \vdots \\ f[Ant_{n,1} & Ant_{n,2} & \cdots & Ant_{n,d}] \end{bmatrix} \tag{3}$$

$M_{antlion}$ and M_{OAL}, shown in Eq (4) and (5), display the ant-lion's location and fitness.

$$M_{antlion} = \begin{bmatrix} AntL_{1,1} & AntL_{1,2} & \cdots & AntL_{1,d} \\ AntL_{2,1} & AntL_{2,2} & \cdots & AntL_{2,d} \\ \vdots & \vdots & \cdots & \vdots \\ AntL_{n,1} & AntL_{n,2} & \cdots & AntL_{n,d} \end{bmatrix} \tag{4}$$

$$M_{OAL} = \begin{bmatrix} f[AntL_{1,1} & AntL_{1,2} & \cdots & AntL_{1,d}] \\ f[AntL_{2,1} & AntL_{2,2} & \cdots & AntL_{2,d}] \\ \vdots & \vdots & \cdots & \vdots \\ f[AntL_{n,1} & AntL_{n,2} & \cdots & AntL_{n,d}] \end{bmatrix} \tag{5}$$

A high probability is obtained for the group of ants that is used to find the best ant lion by using the roulette wheel. For the purpose of trapping, Eqs (6) and (7) are employed.

$$C_i^t = Antlion_j^t + C^t \tag{6}$$

$$d_i^t = Antlion_j^t + d^t \tag{7}$$

Where C_i^t and d_i^t, respectively, represent the ant i's minimal and maximum variables at iteration t. The symbol $Antlion_j^t$ denotes the position of the selected ant lion. The ant lion slides the ant towards it by shooting the sand outward, as seen in Eqs (8) and (9):

$$C^t = \frac{C^t}{I} \tag{8}$$

$$D_i^t = \frac{d^t}{I} \tag{9}$$

where $I = 10^{\omega \frac{t}{T}}$; The symbols t and T denote the current and maximum iterations, respectively. The ant gets grabbed by the ant lions after reaching the bottom of the pit during the last stage of the hunt. Eq (10) is then used to update the position.

$$Antlion_j^t = Ant_i^t \quad if \quad f(Ant_i^t) > f(Antlion_j^t) \tag{10}$$

As demonstrated in Eq (11), the optimum solution must be minimized:

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \tag{11}$$

R_A^t and R_E^t are the random walks that were chosen using a roulette wheel to be near the ant lion.

4.2. Mayfly optimization

In the event of a feeder fault, the Mayfly optimization technique is used to restore service to healthy zones. The network is being reconfigured to restore service to healthy zones. The system is reconfigured after generating a random population (tie switches). Out of all the reconfigured networks, the one with a radial structure that obeys the constraints is chosen, while the others are rejected. The load balancing index (LBI) is calculated for each reconfigured network, and the one with the lowest LBI value is the best solution. The converter's duty cycle is set by the IMO's users, and the IMO's result is the control signal, which is a measure of fertility rate effectiveness. The male mayflies will also perform better in enhancement because they are dependably powerful. The variables' positions are changed by the MO technique depending on their existing positions, using the same settings as the optimization algorithms and velocity at the present epoch. All these mayflies should shift their positions using Eq (12). On the other hand, its velocity might receive a variety of modifications.

$$p_i(t+1) = p_i(t) + v_i(t+1) \tag{12}$$

4.3. Movements of mayflies

Actual fitness $f(x_i)$ and greatest fitness in the previous movements $f(x_{h_i})$ have changed the velocity. If $f(x_i) > f(x_{h_i})$, the previous best movements are listed in Eq (13):

$$v_i(t+1) = g.v_i(t) + \alpha_1 e^{-\beta\gamma_p^2}[x_{h_i} - x_i(t)] + \alpha_2 e^{-\beta\gamma_g^2}[x_g - x_i(t)] \tag{13}$$

g is declared as variable; α_1, α_2 and β are referred as stable. The Cartesian spacing is referred as γ_p and γ_g that is declared in Eq (14):

$$\| x_i - x_j \| = \sqrt{(\sum_{k=1}^{n}(x_{ik} - x_{jk})^2} \quad If \quad f(x_i) < f(x_{h_i}) \tag{14}$$

Male mayflies may have been adjusting their velocity based on their real state, according to the non-systematic dance component d described in Eq (15):

$$v_i(t+1) = g.v_i(t) + d.\gamma_1 \tag{15}$$

4.4. Female mayfly's motion

Mayflies could modify their movements in a distinguishable way. It was anxious to connect with male mayflies in order to breed. The lifespan of female species ranged from one to seven days, and they lack wings. They could therefore alter their velocities based on which male mayflies they wanted to capture. The MO method said that the most physically fit female and male mayflies had to reproduce first; other female and male mayflies may have soon followed, etc. Therefore, if $f(y_i) < f(x_i)$, Eq (16) is written as:

$$v_i(t+1) = g.v_i(t) + \alpha_3 e^{-\beta\gamma_{mf}^2}[x_i(t) - y_i(t)] \tag{16}$$

As an alternative constant α_3 is specified and cartesian distance is denoted by the symbol γ_m, if $(y_i) < f(x_i)$, the female animals alter their movements until the present one runs through additional dance coefficients, hence fl is expressed as Eq (17):

$$v_i(t) = g.v_i(t) + fl.\gamma_2 \tag{17}$$

The indiscriminate values are denoted as γ_2.

4.5. Mating of mayflies

The mayflies in the top half have the capacity to mate and give birth to two or even more young. The way Eqs (18) and (19) are written implies that their offspring can emerge from their mothers at a random rate.

$$offspring1 = L \times male + (1-L) \times female \tag{18}$$

$$offspring1 = L \times female + (1-L) \times male \tag{19}$$

L is represented as Gauss distribution.

4.6. Improved mayfly

Eqs (15) and (17) show that, under certain conditions, members of a swarm change their velocities at random. Effective systems might be utilised to adjust the velocities in other circumstances. Eqs (13) and (16) modified velocities by using balanced current velocities and an incremental weighted length from them to the overall best option, previous best movements, or their spouses. Eq (20) shows how, given more context, the corrected distance portions appear like this:

$$v_p = \alpha_i e^{-\beta\gamma_j^2}(p_j - p_i) \tag{20}$$

Equation (20) must be changed to account for such a scenario, as indicated in the following equation (21):

$$v_p = \alpha_i e^{-\frac{\beta}{\gamma_j}} (p_j - p_i) \tag{21}$$

4.7. Algorithm

1. Read the resistance, reactance, bus load, and zone load input data.
2. Examine the feeder for overload or a fault.
3. If any of the feeders is overloaded. Determine which feeder is overloaded and go to step 4. If a fault occurs on any of the feeders, go to step 12.
4. . Set the population, maximum number of iterations, and ALO parameters to their initial values.
5. Generate a random population of ants and antlions. Out of the 16 switches that are available for the IEEE 3 feeder system , the algorithm randomly chooses any three switches (that are to be operated as tie switches).
6. Reconfigure the system.
7. Check to see whether the reconfigured network is radial. If yes, compute the load balancing index and choose the one with the lowest LBI value as the elite. If not, go to step 6.
8. Utilizing the roulette wheel criteria Choose an antlion, then random walk for the antlion, then update the positions of all ants.
9. Evaluate the fitness (LBI) of all ants after their positions have been updated.
10. If the fitness (LBI) value is lower, replace the elite with it.
11. If the maximum number of iterations are reached, print the elite (the LBI with the lowest value).
12. Create an initial population of male mayflies (tie switches) and assign the maximum number of iterations.
13. Reconfigure the system.
14. Check, if the reconfigured network is radial or not. If yes, calculate the load balancing index and select the one with least value of LBI as global best. If no, go to step 13.
15. Update the male and female mayflies' position and velocity.
16. Calculate fitness (LBI) and rank the mayflies.
17. Use levi flight to determine the velocity of may fly. calculate the gravity coefficient and measure the offspring.
18. Randomly divide offspring into male and female Mayflies. Replace inferior solutions with superior ones (least value of LBI)
19. Update Pbest and Gbest.
20. If the maximum number of iterations reached print the optimal solution the one with least value of LBI.

5. Results and Discussion

The proposed ALO-IMO technique is used on an IEEE 3-feeder test system for load balancing and service restoration, as well as on an IEEE 4-feeder test system for service restoration. The results of these tests are listed below.

5.1. Load balancing in IEEE 3-feeder system

The proposed technique has been validated using an IEEE 3-feeder system (Figure 1). It is made up of three feeders, each with a loading capacity of 15 MVA. There are 13 sectionalizing switches (straight lines) and three tie switches (i.e., dotted lines).

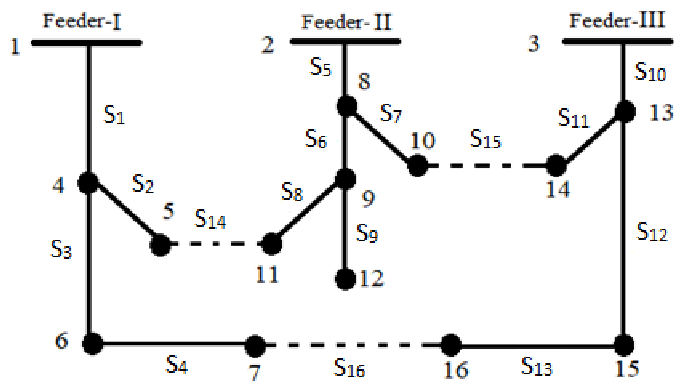

Figure 1: *IEEE 3-feeder system*

The load data for IEEE 3-feeder system is shown in Table 1:

Table 1: *Load data for IEEE 3-feeder system*

From bus-bus	R(ohms)	X(ohms)	End bus load (MW)	End bus load (MVAR)
1-4	0.075	0.10	2.0	1.6
4-5	0.08	0.11	3.0	1.5
4-6	0.09	0.18	2.0	0.8
6-7	0.04	0.04	1.5	1.2
2-8	0.11	0.11	4.0	2.7
8-10	0.08	0.11	5.0	3.0
8-9	0.11	0.11	1.0	0.9
9-11	0.11	0.11	0.6	0.1
9-12	0.08	0.11	4.5	2.0
3-13	0.11	0.11	1.0	0.9
13-14	0.09	0.12	1.0	0.7
4-6	0.09	0.18	2.0	0.8
3-13	0.11	0.11	1.0	0.9

The loading on Feeder-I, Feeder-II, and Feeder-III was 9.912 MVA, 17.426 MVA, and 6.185 MVA, respectively, before reconfiguration. Feeder-II is overloaded by 2.426 MVA when the tie switches operated are S14, S15, and S16. The proposed technique is implemented on the IEEE 3 feeder system for load balancing. The proposed method eliminates the configurations that are not radial and where the feeder limits are exceeded out of the total 16C3 (540) number of combinations. Out of the feasible solutions, the one with the lowest value of LBI is returned by the proposed technique. The loading for feeders I, II, and III after reconfiguration is 12.030 MVA, 12.801 MVA, and 11.027 MVA, respectively. Figure 2 depicts the optimally reconfigured network. The operating tie switches are S7, S8, and S13, with the lowest LBI value of 0.015.

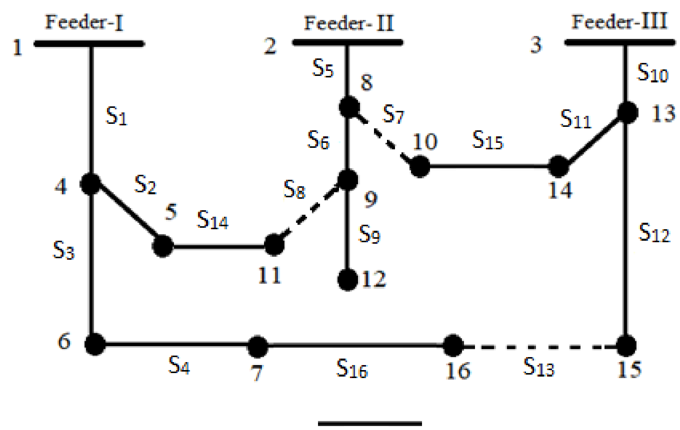

Figure 2: *IEEE 3-feeder system after reconfiguration*

In Table 2, the results of this technique are compared to those of Artificial Ant Colony Optimization [8] and Artificial Bee Colony [9].

Table 2: *Comparison of results with other methods*

S. No	Tie switches	LBI
1	AACO [9]	0.027
2	ABC [8]	0.042
3	Proposed ALO-IMO	0.015

5.2. Restoring service in IEEE 3-feeder system

Figure 3 depicts the IEEE 3-feeder system. The feeder limits are 15 MVA, 30 MVA, and 10 MVA. Table 3 displays the zone load information.

All tie switches are initially open, while all sectionalizing switches are initially closed. In this situation, zone 12 is regarded as a faulty zone, and zone 13 must get service again. An improved Mayfly algorithm is used to find the best solution. The algorithm is designed to eliminate infeasible solutions that do not obey radial configuration and solutions with overloaded feeders. The LBI values for all feasible solutions are calculated, and the algorithm returns the solution with the lowest LBI value as the optimal reconfiguration. The final configuration meets all the conditions of the mayfly algorithm, including the closing of switches S14, S15, and S16 and the opening of switches S5, S9, which have the lowest LBI value of 0.067.

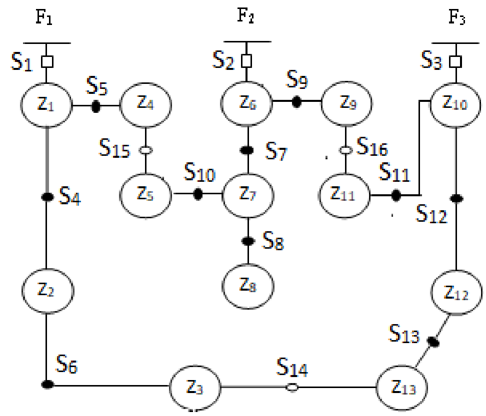

Figure 3: *IEEE 3-feeder system*

Table 3: *Zonal loads for the IEEE 3-feeder system*

S. No	Tie switches	LBI
1	1	2.32
2	2	2.15
3	3	1.92
4	4	3.35
5	5	1.25
6	6	4.82
7	7	5.83
8	8	4.92
9	9	1.34
10	10	1.34
11	11	1.22
12	12	1.34
13	13	2.32

5.3. Restoring service in IEEE 4-feeder system

The proposed ALO-IMO method has been tested using the IEEE 4-feeder system (Figure 4). The system consists of 15 tie switches labelled T1 through T15, as well as 16 sectionalized switches. Every loading feeder has a capacity of 10 MVA. S1, S6, S11, and S16 are the circuit breakers for the system's four feeders. Table 4 depicts the zone loads of an IEEE 4 feeder system.

A permanent fault is anticipated in Zone 13. This has resulted in the supply being turned off for zones 14 and 15. Due to the fault, tie switches 17 and 26 cannot ever be closed, so sectionalizing switches 13 and 14 are always open. Now, the main objective is to bring zones 14 and 15 back into service. The proposed technique can accomplish this. The algorithm is designed to eliminate infeasible solutions that do not obey radial configuration and solutions with overloaded feeders. The LBI values for all feasible solutions are calculated, and the algorithm returns the solution with the lowest LBI value as the restoration path. Service is restored to zones 14 and 15, including zone 20, via feeder F2, which has the least load balancing index value.

Out of all possible solutions, Table 5 displays twelve configurations with low LBI values for

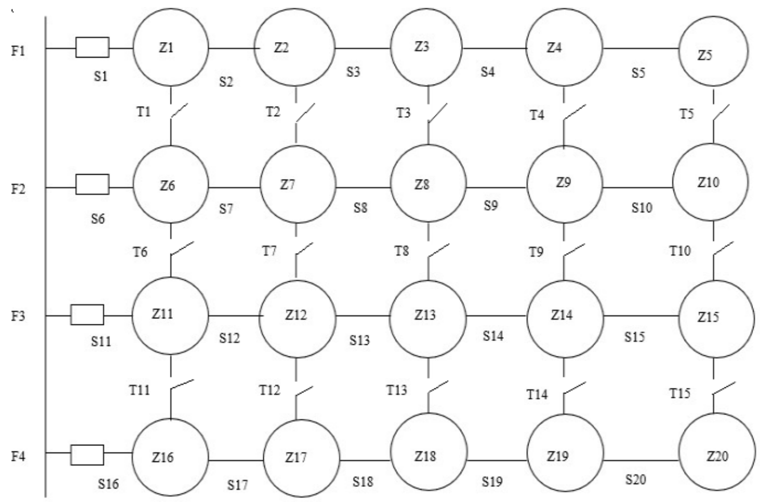

Figure 4: *IEEE 4-feeder system*

Table 4: *Zonal loads for the IEEE 4-feeder system*

S. No	Zone	Load (MVA)
1	1	1600
2	2	700
3	3	1800
4	4	500
5	5	1900
6	6	500
7	7	1500
8	8	1000
9	9	500
10	10	800
11	11	3000
12	12	3500
13	13	700
14	14	1000
15	15	600
16	16	1500
17	17	2000
18	18	1800
19	19	1500
20	20	500

restoring service in an IEEE 4 feeder system.

Table 5 shows that closing the switches T9 and T15 and opening the switch S20 results in the lowest LBI value. This configuration is the best option for restoring service. Figure 5 shows the optimally reconfigured network for restoring service in the IEEE 4 feeder system for a fault in zone 13.

Table 5: *Switches operated and LBI Values for few feasible configurations*

S. No	Switches closed	Switches open	LBI
1	T4, T9, T15	S9, S15	0.143
2	T9, T15	S15	0.046
3	T9, T15	S18	0.046
4	T4, T9, T15	S9, S20	0.122
5	T9, T15	S20	0.007
6	T14		0.081
7	T15		0.081
8	T9		0.024
9	T4, T9	S9	0.115
10	T9, T14	S19	0.109
11	T9, T15	S19	0.109
12	T5	S18, S20	0.046

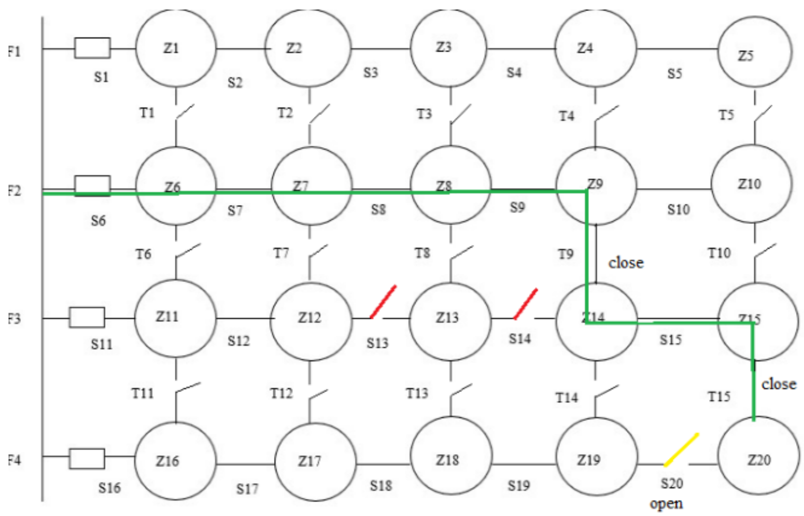

Figure 5: *IEEE 4-feeder system after reconfiguration*

6. Conclusion and Future Work

A hybrid ALO-IMO technique was developed and implemented for load balancing and restoring service on an IEEE 3-feeder system. The proposed technique achieved optimal network reconfiguration in both cases (lowest value of LBI). For restoring service, the proposed technique is also implemented on an IEEE 4-feeder system. When compared to other methods, the optimal network reconfiguration with a 0.007 value for LBI is achieved. In the future, using network reconfiguration, the proposed algorithm can be used to address real, reactive, and apparent power loss.

Declaration of interest: None

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