A Novel Combination of Genetic Algorithm, Particle Swarm Optimization, and Teaching-Learning-Based Optimization for Distribution Network Reconfiguration in Case of Faults

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ABSTRACT

Reconfiguring distribution networks involves modifying their topological structure by managing switch states. This process is crucial in smart grids, as it can isolate faults, minimize power loss, and enhance system stability. However, in existing research, the reconfiguration task is often treated as a problem of either single- or multi-objective optimization and frequently overlooks the issue's multimodality. As a result, the solutions derived may be inadequate or unfeasible when facing environmental changes. In this study, the objective function of minimizing power loss considers the case of faults in the distribution grid. Coordinating the initial population division of the Genetic Algorithm (GA) with the Particle Swarm Optimization (PSO) and the Teaching and Learning-Based Optimization (TLBO) algorithms accelerates the process of finding the optimal solution, resulting in faster and more reliable results. The proposed method was tested on the IEEE-33 bus test system and was compared with other methods, demonstrating reliable results and superior efficiency.

Keywords-genetic algorithm; particle swarm optimization; teaching-learning-based optimization; reconfiguration distribution network; power loss reduction

I. INTRODUCTION

With the advancement of industry and technology, distribution networks have become more complex due to the presence of dispersed energy sources and the diversity of load characteristics. An increase in the rate of incidents impacts electrical safety and customer satisfaction, as well as the economic benefits of electricity-selling enterprises. Reconfiguration of the distribution network in the event of an incident is an effective solution that involves adjusting the network configuration to ensure power supply and optimize economic operations [1-2]. Typically, the reconfiguration of distribution networks falls into two specific categories: (1) adjusting the distribution networks under standard conditions for better economic performance, and (2) reconfiguring distribution networks due to faults [3]. When faults occur, this reconfiguration involves altering the network's topological layout by modifying switch positions. In [4], the reconfiguration in response to faults in the distribution network was to boost its self-healing capacity. As such, this reconfiguration is vital for both elevating the system's reliability [5] and optimizing power flow distribution [6-7]. While it poses a complex optimization challenge, many research approaches address it as either a single-objective or multi-objective optimization task. In [8], a reconfiguration model was developed for distribution networks under fault conditions, aiming to reduce power losses in the grid. A Genetic Algorithm (GA) with an enhanced mutation process was employed to address the reconfiguration issue when faults occur, and its results were validated using the IEEE 33-node distribution system. In [9], a multi-objective reconfiguration challenge was put forth for the electrical distribution network. Following that, an improved multi-objective evolutionary algorithm, grounded in Bayesian probabilistic learning, was utilized to tackle the highlighted challenge.

In [10], the Root Running Algorithm (RRA) was proposed to address the Distribution Network Reconfiguration (DNR) issue. This algorithm incorporates random jumping steps and reinitialization strategies to prevent falling into local minima, and simulation results highlighted its remarkable efficacy in tackling the DNR problem. Many studies leveraged GA to optimize network configurations to reduce losses and switching operations [11]. Alternative metaheuristic algorithms, such as Particle Swarm Optimization (PSO), have been introduced to address this and enhance solution quality, especially to evade local optima. PSO has shown notable success in optimization, directing a population of particles using historical performance data. Its applications in DNR are varied, from enhancing load balancing to quality-performance trade-offs. In [12-13], a discrete PSO algorithm was proposed for DNR, noting its computational intensity due to nonradial solutions. In [14-16], GA was utilized to decrease power loss and enhance electrical system reliability. Despite GA's proficiency with discrete variables and nonlinear objectives, its time efficiency remains a concern, and not all problems are amenable to GA solutions. Enhanced PSO variants have been developed to accelerate the search by incorporating historical solutions [17]. In [18], the Niche-Binary PSO (NBPSO) aims to avoid the issue of premature convergence endemic to standard PSO [19]. In [20], binary PSO was explored. In [21-23], artificial neural networks were used to optimize power loss. In [24], the gravitational optimization algorithm was used for the reconfiguration problem with multi-objective goals, such as reducing losses and operational costs. The reconfiguration process impacts not only power losses but also several other aspects of the distribution network. In [25], an enhanced heuristic method based on the branch exchange technique was utilized to address the problem, aiming to reduce loss costs, switch operation costs, and improve node voltage levels. The branch exchange method was refined to consistently produce valid network configurations without the need to solve the closed-network power distribution problem. In [26], a multi-objective heuristic method, the Fuzzy Multiobjective Approach (FMA), was introduced to target loss reduction, voltage deviation, and load balance across branches and feeders. Furthermore, some studies successfully employed generic heuristic algorithms for multi-objective reconfiguration, such as GA, and simulations demonstrated its ability to efficiently converge with a reduced population.

Unlike the previous studies, this one considers not only multi-objectives in the reconfiguration during distribution network incidents but also other objectives. As a result, solution outcomes might encompass multiple configurations to meet the problem's objectives, aiding operation engineers in selecting a distribution network structure to operate during malfunctions. However, local optimization and extended computation times pose challenges for numerous multi-objective evolutionary algorithms proposed in previous studies. Therefore, this issue continues to attract researchers' attention. To solve this problem, this study proposes an optimization method that combines the advantages of GA, PSO, and the Teaching-Learning-Based Optimization (TLBO) algorithm. The proposed technique was tested on the IEEE 33-node sample grid and compared with several other methods, demonstrating reliable results and improved computation speed.

II. MODEL AND CONSTRAINT CONDITIONS

The problem of reconfiguring the distribution grid in the event of a fault is a complex nonlinear optimization issue on a large scale and is dynamic due to the unpredictability of the fault location. Additionally, the objective function aims to reduce energy losses and voltage deviation errors, ensuring constraints on online loading capacity, power balance, and the radial operation of the distribution network.

A. The Objective Function

Based on [4, 8, 11], energy losses and voltage deviation errors are commonly used as objective functions in the reconfiguration of distribution networks. These two objectives can help minimize system losses and maintain network stability. Therefore, energy losses and voltage deviation errors are the two objective functions. The objective function for power loss on the distribution network is given by:

$$F_1 = \min(\sum_{ij=1}^{N} k_{ij} R_{ij,} \frac{P_{ij}^2 + Q_{ij}^2}{U_j^2}) \quad (1)$$

where N is the number of branches on the distribution network, k_{ij} is the status of the branch (k_{ij} equals 0 if the branch is open and 1 if it is closed), R_{ij} is the resistance of branch ij, P_{ij} is the active power on branch ij, Q_{ij} is the reactive power on branch ij, and U_j is the voltage at node j.

B. Constraint Conditions

The technical assurance conditions for distribution networks include the following:

Conditions to balance node active and reactive power:

$$P_{Gi} - P_{Si} - P_{di} = 0 \;\; \forall\, i \in \Omega_b \quad (2)$$

$$Q_{Gi} - Q_{si} - Q_{di} = 0 \;\; \forall\, i \in \Omega_b \quad (3)$$

Condition to ensure allowable voltage limits:

$$U_{min} \leq U_i \leq U_{max} \;\; \forall\, i \in \Omega_b \quad (4)$$

Condition to ensure current flow on branch ij:

$$I_{ij} \leq I_{ijmaxcp} \quad (5)$$

Condition to a radial structure for the distribution network:

$$h_k \leq H_k \quad (6)$$

where P_{Gi} is the active power generated at node i (pu), Q_{Gi} is the reactive power generated at node i (pu), P_{Si} is the total active power demanded at substation i (pu), Q_{Si} is the total reactive power demanded at substation i (pu), P_{di} is the total active power demanded at node i (pu), Q_{di} is the total reactive power demanded at node i (pu), Q_{Gi} is the reactive power generated at node i (pu), h_k is the restructured network structure, and H_k is the set of distribution grid structures that can be implemented according to the operating rules of the distribution network.

III. METHODOLOGY

A. Introduction to GA, PSO, and TLBO

1) Genetic Algorithm's (GA) Overview

GA was introduced as a stochastic search technique inspired by Darwin's theory of evolution [27]. GA is a probabilistic search method modeled on the principle of natural selection [13]. It initiates its search with a collection of population strings, each representing a potential solution within the predefined search domain. Mimicking biological evolution, GA generates new candidate solutions, termed offspring, from the preceding generation of parents. However, their exploratory capabilities can sometimes constrain GAs, resulting in slower convergence rates or suboptimal robustness [19]. This limitation makes them susceptible to premature convergence and entrapment in local optima, particularly in complex optimization scenarios.

2) Particle Swarm Optimization (PSO) Overview

PSO is a more recent addition to evolutionary computational techniques [28]. Drawing inspiration from the social behaviors of bird flocking or fish schooling, PSO features a group of particles, also known as potential solutions, that traverse the multi-dimensional solution space. The trajectory of each particle is influenced by its personal best position and the optimum found by its neighbors. Unlike GA, PSO employs the entire group of solutions from start to finish, adhering to the survival of the fittest doctrine. However, PSO shares similar drawbacks as GA, including issues with convergence speed and robustness.

3) Teaching-Learning Based Optimization (TLBO) Overview

TLBO is modeled after the interaction between a teacher and students in a classroom setting [29]. It encapsulates the concept of mutual learning, where individuals learn from a teacher and each other. TLBO is a population-based algorithm that views solution vectors as a class of students learning various subjects, analogous to manipulating different decision variables in an optimization problem. The algorithm employs two primary modes of learning: the teacher phase for global search, where the best solution acts as a teacher, and the learner phase for local search, where learners exchange knowledge among themselves. Through iterations, the population hypothesizes and converges toward the best global solution for the problem at hand.

4) Combining Algorithms

The flexibility of GA and PSO for nonlinear optimization problems has been analyzed and evaluated in many studies. Recent studies have indicated that a hybrid metaheuristic approach, integrating multiple strategies, is more effective than employing a single algorithm. This study introduces a GA-PSO-TLBO hybrid method, leveraging GA's global search capabilities, PSO's local search efficiency, and TLBO's learning mechanism, and validates its efficacy against conventional single and hybrid methods. The proposed method was used to solve the problem of minimizing power loss while electrical distribution networks are rearranging during faults. This study makes important contributions by introducing a useful hybrid metaheuristic approach and showing that it is robust, especially when investigating changes in population size and offspring generation in the TLBO process.

B. Combining GA-PSO-TLBO for the Reconfiguration Problem in Case of Fault

Applying a single optimization method to a problem is not as effective as leveraging the combined strengths of various optimization techniques [30]. This study proposes the GA-PSO-TLBO method to effectively address optimization problems with many discrete variables. The GA-PSO-TLBO method effectively combines the benefits of three different optimization techniques in its search process to enhance its problem-solving performance.

The GA method initiates its search by generating a random population. This population is made up of individuals with various fitness values, granting it global search capability. This ensures that the GA has a higher likelihood of identifying the optimal solution compared to local search strategies such as SA and HC. However, since GA is rooted in a population-based search and utilizes operations (such as selection, crossover, and mutation) on the entire population, it may exhibit slower convergence tendencies [30]. To address this shortcoming of GA while still embracing a population-based search, an effective strategy could be to operate it on just a selected number of individuals rather than the whole group. This study used the top 50% of the initial population based on higher fitness values for the GA cycle. The rationale behind this is that leveraging the top 50% with higher fitness scores increases the probability of pinpointing the optimal solution compared to relying on those with lower fitness scores. The GA's search mechanism can counteract the potential issue of early convergence caused by significant similarities in the top-performing subset. The global search capability of GA serves to diversify the individuals in the group. On the contrary, using the subset with lower fitness values could reduce the probability of discovering the optimal solution [20]. This implies that if GA initiates its search with a population subset of lesser fitness values, it has a reduced chance of identifying the optimal solution. GA's approach of exploring a vast spectrum of values to boost individual diversity contributes to this. As a result, there is a pressing need to minimize the diversity within the subset that has lower fitness values to expedite the path to the optimal solution.

Implementing PSO in this lesser-performing group can be an effective strategy, given its ability to rapidly enhance the fitness values of current members based on their velocities and positions [20, 23]. This study uses the bottom 50% of the initial population based on lower fitness values for the PSO cycle. The reason behind this decision is that the PSO's search mechanism can enhance the fitness values of individuals in this subset, making the PSO a suitable method for swiftly pinpointing the optimal solution. Furthermore, it has been indicated [20, 23] that applying the TLBO search process to elite members following the GA search can lead to further enhancements. Given that GA does not provide substantial learning capabilities for its elite members during its search, introducing the TLBO search process to a select group with higher fitness scores can increase the probability of identifying the optimal solution. In this context, the top 50% of offspring, derived post-GA and PSO cycles, are used for the TLBO search phase. Figure 1 shows the flow chart of the proposed method. An initial population is randomly generated and divided into two subpopulations: 50% with higher fitness values and 50% with lower ones. These subpopulations are then fed into the GA and PSO loops, respectively. GA aims to diversify the population, while PSO aims to accelerate the search for the best solution. Integrating both GA and PSO boosts exploration and exploitation simultaneously. From the combined offspring of GA and PSO, 50% with higher fitness values are used in the TLBO loop, which aims to enhance the likelihood of pinpointing the optimal solution.

IV. RESULTS AND DISCUSSION

The proposed algorithm was implemented in MATLAB 2019a, running on a PC with an i7 processor at 6 GHz, and applied to a 33-node distribution system. Comparative analysis was performed based on distribution losses, node voltage values, fitness values, convergence iteration counts, and the time taken to execute the optimization process.

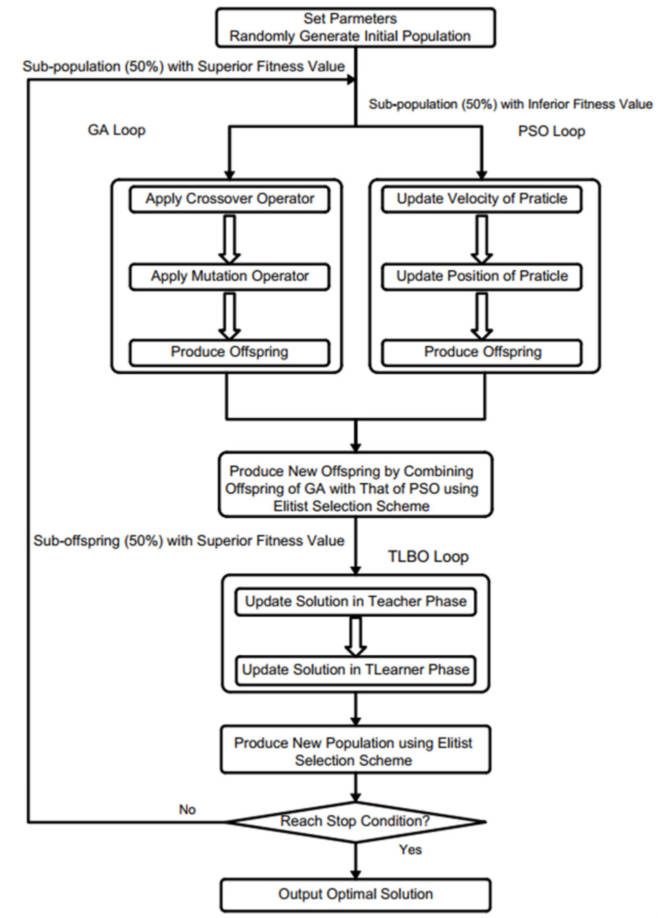

Fig. 1. Flowchart of the proposed GA- PSO-TLBO algorithm.

A. System Main Process

The main steps of the simulation process are executed as shown in Figure 3.

- Step 1: Update the operational parameters of the distribution network.
- Step 2: Simulate a fault at a location on the distribution network.
- Step 3: Identify the fault location and the nodes that are isolated (de-energized).
- Step 4: Update the distribution network parameters in the event of a fault.
- Step 5: Find the optimal configuration using the proposed GA-PSO-TLBO algorithm.
- Step 6: Calculate the established mode for the new configuration and check the constraint conditions.

```
Initialize the vector x_k as the state of the
switches, where x_i has a value of 0 (switch open) or
1 (switch closed), following the formula:
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$$x_k = \underbrace{x_1, x_2, \ldots, x_m}_{50\%\ for\ GA} \underbrace{x_{m+1}, x_{m+2}, \ldots, x_n}_{50\%\ for\ PSO}$$

```
Input: problem data(f(x),n),
parameters:maxGen,k:popSz, rand:random number);
output: the best solution G_Best;
begin:
t ← 0;
randomly generate parent population P(t)=[x_k(t)];
evaluate P(t) and keep the best solution I_best in
P(t);
while(not terminating condition)do
 create P_1(t)using superior solutions(50%)from P(t);
//P_1(t)=[x_k/2(t)]
 create P2(t) using inferior solutions (50%) from
 P(t); //P_2(t) =[x_k/2(t)]
 create G(t+1)from P_1(t) by crossover routine;
//G(t+1)=[x_k/2(t)], GA population // GA loop
 create G(t+1) from P_1(t) by mutation routine;
 evaluate G(t+1) and keep the best solution GA_best in
 G(t+1);
 PSO_best ← big M; //PSO loop
 for each particle x_k(t) in swarm of P_2(t) do
  update velocity v_k(t) by v_k(t+1) = w.v_k +
    c_1d_1(lbest_k - x_k) + c_2d_2(xBest(t) - x_k);
  update position x_k(t+1) by x_k(t+1) = x_k(t) +
v_k(t+1);
  S(t+1)← x_k(t+1); //S(t+1)=[x_k/2(t)] //PSO
population
  if PSO_best>f(x_k(t+1))then
   PSO_best = x_k(t+1);
  end
 end
 create offspring using G(t+1) and S(t+1); //TLBO
 create L(t+1) using 50% superior solutions from
  offspring; //L(t+1)=[x_k(t)], TLBO population
 select teacher value X_best and calculate the mean of
 the class X_mean in L(t+1);
  for k=1 to popSz/2
   T_f =round(1 + rand(0,1)) //Teacher phase
   x_k(t+1)^new= x_k(t+1) + rand(X_best - T_f.X_mean)
   if f(x_k(t+1)) > f(x_k(t+1)^new) then
    x_k(t+1) = x_k(t+1)^new
   end
   randomly select a learners x_p from {1,2,…,popSz};
   //Learner phase
   if(x_k(t+1) > f(x_p)) then
    x_k(t+1)^new = x_k(t+1)+rand(x_k(t+1)-x_p)
   else
    x_k(t+1)^new = x_k(t+1)-rand(x_k(t+1)-x_p)
   end
   if f(x_k(t+1))> f(x_k(t+1)^new) then
    x_k(t+1) = x_k(t+1)^new
   end
   select X_best and calculate X_mean in L(t+1);
 end
 TLBO_best = X_best
 G_best=argmin{I_best, GA_best, PSO_best,TLBO_best}
 reproduce P(t+1) from G(t+1), S(t+1), and L(t+1) by
 elitist selection routine;
 t ← t+1;
end
output: the best solution G_Best
end;
```

Fig. 2. The pseudocode of the proposed algorithm.

B. Parameter Setting of the IEEE-33 Bus

Figure 4 shows the IEEE-33 bus distribution system that was used to validate the performance of the GA-PSO-TLBO algorithm. The system consists of 33 nodes, 32 section switches, and 5 interconnection switches [11]. This system operates at a base voltage of 12.66 kV. In the initial state of the distribution network before any fault onset, switches 33-37 are open, while the rest remain closed. The initial power loss is 191 kW, with a voltage deviation of 0 pu [11]. The parameters of the GA and PSO search align with those mentioned in [8]. For all algorithms, the maximum function evaluations and population size were set at 500 and 200, respectively.

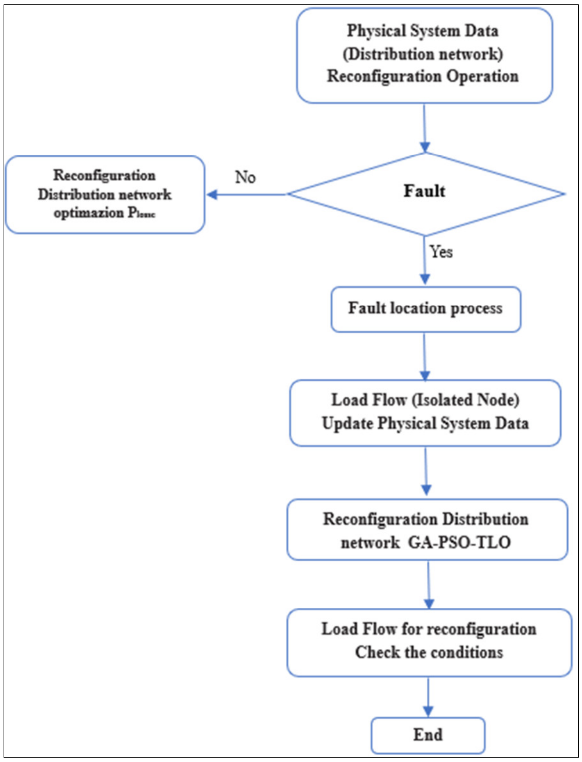

Fig. 3. Steps to perform the simulation process.

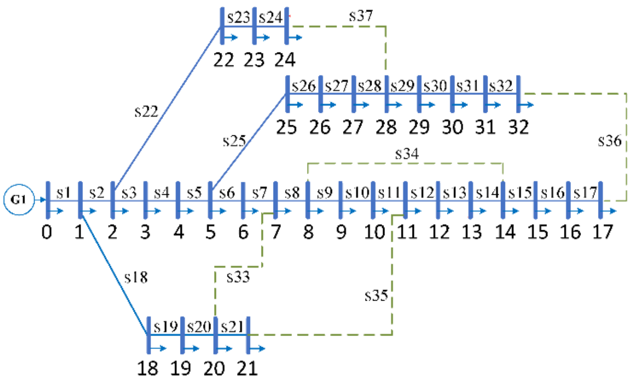

Fig. 4. IEEE 33-bus distribution system and initial state.

C. Simulation Results

Identifying equivalent schemes is essential in the process of resolving fault reconfiguration issues within distribution networks. In this simulation, the efficacy of the GA-PSO-TLBO algorithm was demonstrated using the IEEE 33-bus distribution system framework. Table I proposes test scenarios during the occurrence of a fault in branch 9. Due to the fault at branch 9, nodes 9 to 17 are de-energized, resulting in their voltage values being zero before reconfiguration. After reconfiguration with the objective function aimed at reducing losses, Figure 5 shows that all previously de-energized nodes were re-energized, the minimum node voltage increased, and the voltage quality of the power supply improved across all three considered schemes while maintaining voltage values within acceptable limits (0.9-1.1 pu). The losses associated with the proposed schemes were approximately equal. Based on the above analysis, the proposed method exhibits adaptability to dynamic or uncertain environments, and the equivalent solutions it provides can assist decision-makers in effectively managing unexpected faults, ensuring the completion of the distribution network's fault reconfiguration process without the need to adjust the initial objectives. This also improves the safety and reliability of the electrical supply in the distribution network. Furthermore, the proposed algorithm avoids local optima and offers three schemes that guarantee the satisfaction of the necessary constraints for the objective function and power supply capabilities.

TABLE I. RECONFIGURATION OF THE PROPOSED GA-PSO-TLBO

Case	Fault in branch	Solutions (switch open)	Power loss/100 kW	V_{min}/V_{max}
1	9	6;32;34;37	1.356	0.938/1.00
2	9	7;14;25;32	1.362	0.925/1.00
3	9	7;8;32;37	1.379	0.927/1.00

D. Comparison

Computational efficiency and algorithmic efficacy are important measures to solve real-world engineering challenges. Table II shows a comparison of the time the algorithms take to execute and the quality of the solutions they produce.

TABLE II. TIME AND NUMBER OF ITERATIONS COMPARISON

Case	GA-PSO- TLO (proposed)	SPEA [31]	MOPSO [32]	NSGA-II [33]
Time (s)	48.62	63.91	64.47	35.31
Number of iterations	42	40	39	36
Result	3	1	1	1

Table II consolidates the mean computational duration and the spectrum of solutions discerned by each algorithm. The proposed algorithm was faster than the Multi-Objective Particle Swarm Optimization (MOPSO) and the Strength Pareto Evolutionary Algorithm 2 (SPEA2). The proposed GA-PSO-TLBO method was also better than MOPSO and SPEA2 in finding a wider range of solutions. Although the Non-dominated Sorting Genetic Algorithm II (NSGA-II) had less runtime than the proposed one, it fell short in achieving its breadth in solution discovery. Table II shows that the proposed method is effective, accurate, and reliable. After careful consideration, it can be said that the GA-PSO-TLBO algorithm has a fast calculation speed, proposes optimal operating structures for the operator to choose from, and is therefore suitable for the problem of reconfiguring the distribution network in case of failure.

V. CONCLUSION AND RECOMMENDATIONS

The optimization of fault reconfiguration processes is critical to improving the operational efficiency and dependability of smart grid systems. This study presented the GA-PSO-TLBO algorithm, which combines discrete multimodal multi-objective PSO, GA, and TLBO.

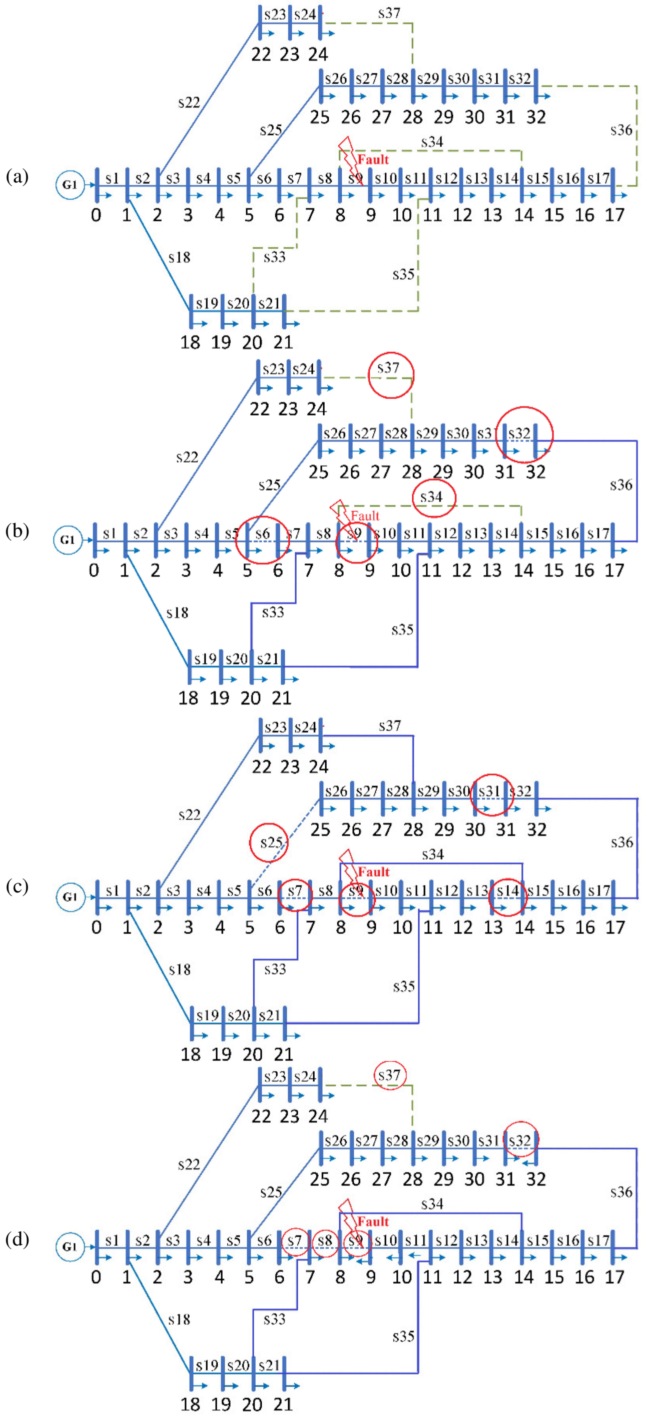

Fig. 5. Reconfiguration schemes of equivalent solution: (a) initial state topology in branch 9, (b) reconfiguration case 1 for the equivalent solution, (c) reconfiguration case 2 for the equivalent solution, and (d) reconfiguration case 3 for the equivalent solution.

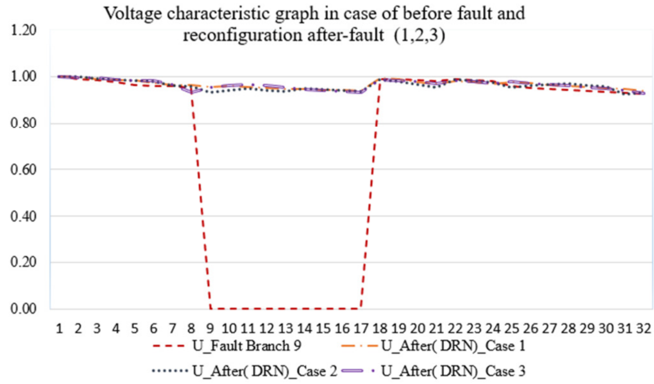

Fig. 6. Voltage values of each node equivalent solution.

This algorithm is specifically designed to address the complexities of fault reconfiguration in electrical distribution networks. This algorithm introduces a novel selection method to optimize the search for robust solutions within the GA-PSO-TLBO framework. The results, simulated in several fault cases, demonstrated that the precision of the proposed method is comparable to that of previous methods, but the convergence speed was enhanced, resulting in accelerated calculation times. The proposed algorithm generates more optimal configurations, which significantly aid decision-making in the operation of distribution networks during electrical faults. A comparative analysis was performed on an IEEE 33-bus against established methods, such as MOPSO, NSGA-II, and SPEA, to substantiate the algorithm's performance. The results showed that the proposed GA-PSO-TLBO algorithm was better suited to help with fault reconfiguration problems in distribution networks. In particular, the GA-PSO-TLBO algorithm excelled in generating a diverse array of feasible solutions in less time, providing decision-makers with a versatile toolkit to navigate emergencies and adapt to dynamic grid conditions.

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