A NOVEL PARTICLE SWARM OPTIMIZATION GUIDED GENETIC TO THE DISTRIBUTION NETWORK RECONFIGURATION PROBLEM WITH AN OBJECTIVE FUNCTION OF MINIMUM OPERATING AND POWER OUTAGE COSTS

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ABSTRACT

In operating the distribution network, the problem of reconfiguration distribution network according to the change of load to reduce power loss has partly reduced the operation cost of the distribution network but it can impact the reliability of power supply to the load. Therefore, in this study, we propose a hybrid algorithm that integrates two well established methods, including the genetic algorithm (GA) and the particle swarm optimization (PSO) algorithm for the problem of reconfiguration distribution network with the objective function of the with the objective function of reducing power loss considering operating costs and power outage costs on the distribution network. To demonstrate the performance of the proposed PSO-GA Algorithm simulations have implemented through MATLAB 2019[a] and PSS/ADEPT software. Utilizing the IEEE 33-bus distribution system for the experiment. The results show that the algorithm provides decision-makers with a range of equivalent options when addressing the challenge of distribution network reconfiguration.

ĐỀ XUẤT ÁP DỤNG GIẢI THUẬT PSO – GA CHO BÀI TOÁN TÁI CẤU HÌNH LƯỚI ĐIỆN PHÂN PHỐI CÓ XÉT ĐẾN TỐI ƯU HÓA CHI PHÍ VẬN HÀNH VÀ CHI PHÍ NGƯNG CẤP ĐIỆN

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TỪ KHÓA

Thuật toán di truyền (GA)
Thuật toán bầy đàn (PSO)
Lưới phân phối
Tái cấu hình lưới điện phân phối
Tối ưu hóa

TÓM TẮT

Trong vận hành lưới điện phân phối, bài toán cấu hình lại mạng lưới phân phối theo sự thay đổi của tải nhằm giảm tổn thất điện năng giúp phần nào giảm chi phí vận hành của mạng lưới phân phối nhưng sẽ ảnh hưởng đến độ tin cậy cung cấp điện của tải. Trong nghiên cứu này, chúng tôi đề xuất một giải thuật kết hợp giữa hai thuật toán đã được chứng minh hiệu quả, đó là kết hợp giải thuật di truyền (GA) và giải thuật tối ưu hóa bầy đàn (PSO) cho bài toán tái cấu hình với hàm mục tiêu là giảm tổn thất công suất có xét đến chi phí vận hành và chi phí ngừng cấp điện trên lưới phân phối. Để chứng minh hiệu suất của giải thuật PSO-GA được đề xuất, mô phỏng đã được thực hiện thông qua phần mềm MATLAB 2019[a], và hệ thống lưới phân phối mẫu IEEE 33- nút được sử dụng trong mô phỏng. Kết quả thực nghiệm cho thấy giải thuật được đề xuất cung cấp các cấu trúc tối ưu khi giải quyết vấn đề tái cấu hình lại lưới điện phân phối khi xét đến chi phí vận hành và ngưng cấp điện.

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1. Introduction

Distribution networks are commonly arranged in a radial structure due to the straightforwardness in managing and modifying such systems. In normal operating conditions, the performance of these networks can be optimized by adjusting the status of sectionalizing and tie switches, while respecting system limitations and striving to achieve operational goals. This optimization procedure is referred to as Distribution Network Reconfiguration (DNR) [1]. Over the past thirty years, extensive research has explored various approaches to address the challenges of DNR. Since this strategy relies on heuristic methods, systematically arriving at the optimal solution poses a challenge. The concept of DNR was originally introduced by [2] as a strategy to reduce losses in feeders Civanlar et al. [3], Baran et al. [4] presented two distinct techniques that vary in their accuracy of simulating power flow in networks.

In contemporary research, meta-heuristic techniques have gained recognition for their capacity to solve complex combinatorial optimization problems and secure globally optimal solutions. Prominent among these methods are the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). The inaugural proposal of a GA-centric approach for Distribution Network Reconfiguration (DNR) was documented in [5], employing string representations to map the states of switches. Nonetheless, the lengthy nature of these strings in extensive networks posed challenges for the GA's search efficiency. Initial trials showed potential in minimizing losses, yet they were marred by lengthy computation times. Subsequent adaptations of the GA for DNR have been developed. Zhu [6] improved GA's performance by altering the representation of the string to only reflect open switches, thereby reducing the string size and incorporating system constraints into the fitness function along with an adaptive mutation strategy to regulate mutation probability. Mendoza et al. [7] proposed a new minimal loss reconfiguration approach, employing fundamental loops and modified genetic operators to manage the search space. Enacheanu et al. [8] combined matroid theory and graph theory with GA for loss minimization in distribution networks. The practice of adaptive GA was explored in [9], employing graph theory to seed the initial population with feasible solutions. Braz and Souza [10], [11] and others have leveraged GA for optimizing network configurations to reduce losses and switching operations. 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. To address this and enhance solution quality—especially to evade local optima—alternative meta-heuristics like PSO have been introduced. PSO has shown notable success in optimization, directing a population of particles by historical performance data. Its applications in DNR have been varied, from enhancing load balancing to quality-performance trade-offs. Sivanagaraju et al. [12] demonstrated a discrete PSO algorithm for DNR, noting its computational intensity due to non radial solutions. Enhanced PSO variants have been developed to quicken the search by incorporating historical solutions [16], and the Niche Binary PSO (NBPSO) aims to sidestep the issue of premature convergence endemic to standard PSO [12].

In this study, the research team developed an objective function to minimize power losses that considers the cost of opening/closing switches on the distribution network. The study suggests the application of a hybrid approach combining Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) for solving the optimization problem. Here, the PSO algorithm is used to direct the initial population generations for the GA, aiming to reduce computation time and ensure the attainment of an optimal solution while avoiding the GA's tendency for local optimization. The research findings have been validated on the IEEE 33-node test system, indicating reliable results that can potentially be applied to real-world distribution networks.

2. Mathematical Model and Proposed Method

The reconfiguration distribution network involves strategically opening and closing sectionalizing and tie switches. This process maintains a radial network topology and ensures continuous power supply to all end-users. Adjusting the network's structure changes the distribution of power across nodes, affects power loss, and impacts the system's overall reliability. The main goals of this reconfiguration are to reduce overloads on lines and transformers, minimize energy losses, and enhance the power supply's reliability. This ultimately aims to decrease the costs associated with power outages.

2.1. Distribution network operating cost

The single-line schematic representation of a distribution line is in the present Figure 1.

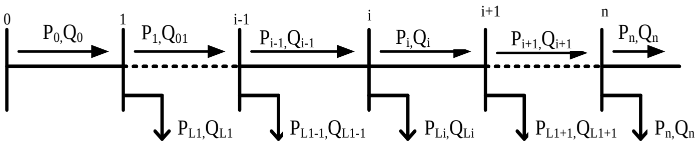

Figure 1. *Single-line diagram of a line*

Sequentially, the active and reactive power values on branch (i+1) are deduced using the given approximate power formulas.

$$P_{i+1} = P_i - P_{Li+1} - R_{i,i+1}\left[\frac{P_i^2+Q_i^2}{|V_i^2|}\right] \tag{1}$$

$$Q_{i+1} = Q_i - Q_{Li+1} - X_{i,i+1}\left[\frac{P_i^2+Q_i^2}{|V_i^2|}\right] \tag{2}$$

The active power loss on the line from node i to i+1 is $\Delta P_{(i,i+1)} = R_{i,i+1}\left[\frac{P_i^2+Q_i^2}{|V_i^2|}\right]$ (3)

The load graph of daily and seasonal load patterns is shown in Figure 2, it shows that the power consumption of the loads varies by hour, by load characteristics and by season.

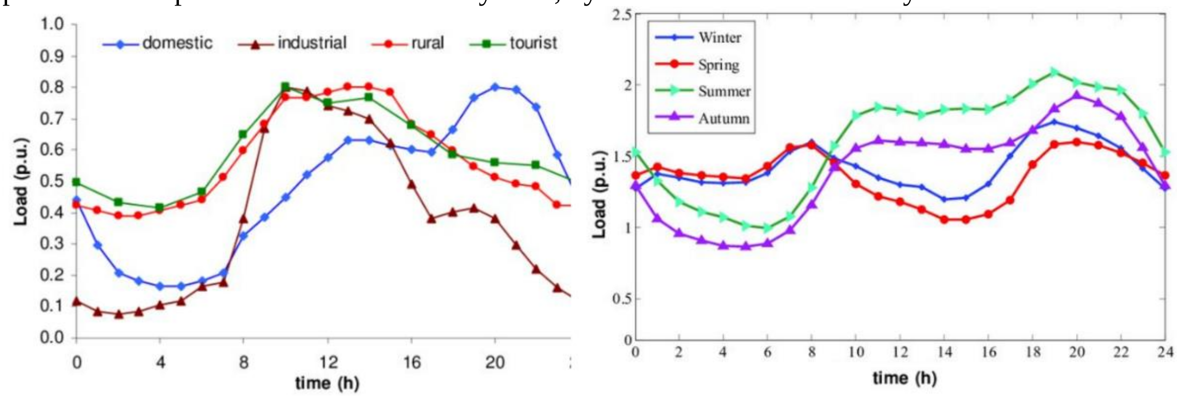

Figure 2. *The graph of daily load for the distribution network in a season*

The operating cost function for the distribution network in one season of the year.

$$Cost_1 = C_0.m.\sum_{j=1}^{24}\Delta P_i t_j = C_0.m.\sum_{j=1}^{n}\frac{P_i^2+Q_i^2}{V_i^2}t_j \tag{4}$$

Where: ΔP_i active power loss at time *ij*; P_i, Q_i : active and reactive power on branch *i*. V_i is the connection node voltage of the branch on branch *i*.

The distribution network must adhere to the constraint that voltage and current levels remain within their prescribed limits.

$$V_{i,min} \le |V_i| \le V_{i,max} \tag{5}$$

$$|I_i| \leq I_{i,max} \tag{6}$$

The pseudocode for calculation the operating costs of the distribution network a season is presented in Figure 3.

```
Start
// Initialize variables if necessary
// e.g., let C0 and m be constants used in cost calculation
// let t_i be the current time interval
// Read data from the load graph
load_data = read_load_graph()
// Solve the power distribution problem using Newton's method
power_distribution_solution = solve_power_distribution(load_data)
// Initialize variable for storing cost
Cost_t = 0
// Loop to calculate cost for each time interval
for t_i = 1 to number_of_time_intervals:
  if t_i != 24:
    // If the current time interval is not the 24th, continue to next iteration
    continue
  else:
    // If the current time interval is 24, calculate the cost
    delta_P_t = calculate_power_difference(power_distribution_solution, t_i)
        // Aggregate power differences over 24-time intervals and divide by m
    for t_j = 1 to 24:
      Cost_t += delta_P_t[t_j]
    Cost_t = C0 * Cost_t / m
    break // Exit the loop as the cost for the required time interval has been calculated.
// Output the cost for the time interval t_i
output(Cost_t)
End
```

Figure 3. *The pseudocode Algorithm for calculating operating costs in a season/year*

2.2. Power outage cost

Consider a simple single-source distribution network in Figure 4.

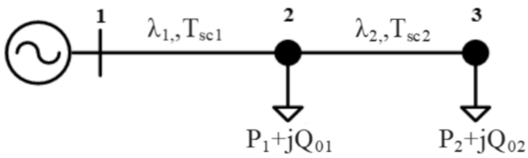

Figure 4. *Diagram of a single-source two-load distribution network*

Assuming that each network section has a section device, the power outage time of each load is as follows: $T_{mđ1} = \lambda_1 T_{sc1}$; $T_{mđ2} = \lambda_2 T_{sc2} + T_{mđ1}$

$$\text{or } T_{mđi} = \lambda_i T_{sci} + T_{mđi-1} \tag{7}$$

Where: λ_i, T_{sci}, and $T_{mđi-1}$ represent fault intensity, fault time at node i, and time of power outage from source, or circuit breaker to node *i – 1*, respectively;

The power that cannot be supplied to customers at the moment is:

$$A = T_{mđ1} P_1 + T_{mđ2} P_2 \tag{8}$$

The power outage cost of the distribution network can be calculated through the damage caused by the fault to customers with interrupted power supply:

$$Cost_2 = C_1 A = C_1 \sum_{i=1}^{n} P_i \lambda_{sci} T_{sci} \quad (9)$$

Where: n is the number of loads in the power network. C_1 is the power unit price at the power outage, also known as the unit price applicable to a violation of the power supply contract of load i (\$/kWh), which is often many times higher than the normal power selling price C_0. A is the amount of power that cannot be supplied to customers. P_i is the active power at node i (kW). T_{sci} is the repair time of load i (h). λ_{sci} is the fault intensity of the load node on the line (times/year).

The steps of the algorithm to calculate the power outage cost are as follows the pseudocode algorithm to calculate power outage cost for each configuration in Figure 5.

```
Start
// Enter grid parameters
grid_params = input("Enter grid parameters (Node parameter, branch, magnitude, and crash time): ")
// Import ray/grid structure
// (This structure is created by changing the electric locks)
ray_grid_structure = import_ray_grid_structure(grid_params)
// Create source set and load set from grid structure
source_set = create_source_set(ray_grid_structure)
load_set = create_load_set(ray_grid_structure)
// Generating source and load file from grid structure
// (The grid structure indicates the ability to connect the grid)
source_load_file = generate_source_load_file(source_set, load_set)
// Calculate outage time for connection set
total_outage_time = calculate_outage_time(source_set, load_set)
// Loop for toggling the download button and updating the source file
while not is_load_empty(load_set):
   // Toggle the newly selected download button (in button)
   // From download file to source file
   toggle_download_button()
   update_source_file(source_load_file)
   // Update the load set as some loads might have been served
   load_set = update_load_set(load_set)
// Check if the load is empty after toggling the download button
if is_load_empty(load_set):
   // Calculate outage costs for existing grid
   total_cost = calculate_outage_costs(grid_params, total_outage_time)
// Output the total cost
output(total_cost)
End
```

Figure 5. *The pseudocode algorithm to calculate power outage cost for each configuration*

2.3. Objective function of the math problem

A functional goal for reconfiguring the electrical network that incorporates considerations of power delivery dependability can be formulated based on the aim to diminish both the operational expenses and the cost implications of power interruptions for consumers, as detailed below:

$$COST = min\{Cost_1 + Cost_2\} = min\{[\alpha_1 C_0 \sum_{j=1}^{24} \Delta P_j t_j].m + C_1 \sum_{i=1}^{n} P_i \lambda_{sci} T_{sci}\} \quad (10)$$

Where: m the number of survey days in a year, P_i the power consumed at node i (kW), ΔP_j is the total power loss on the network at time j, t_j is the survey time in a day, T_{sci} is the repair time of load i (h), λ_{sci} is the fault intensity of load node on the line (times/year or times/season), C_0 is normal power unit price of load i (\$/kWh), C_1 is power unit price at the power outage of load i (\$/kWh), α_1, α_2 are factors for selecting the objective function.

2.4. The proposed application PSO-GA for Objective function

In this study, we explore the synergy of two robust optimization strategies rooted in the principles of natural selection, aiming to address intricate optimization challenges effectively. The two strategies in question, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), are extensively recognized and employed across numerous studies to tackle complex engineering optimization issues. Given the comprehensive discussion of both algorithms in various scholarly publications, this document will briefly review these techniques before delving into the hybrid GA-PSO approach developed herein.

2.4.1. Overview Genetic Algorithm

GA is a probabilistic search methodology modeled on the principle of natural selection, encapsulated by the 'survival of the fittest' concept [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, GAs can sometimes be constrained by their exploratory capabilities, leading to slower convergence rates or suboptimal robustness [15]. This limitation makes them susceptible to premature convergence and entrapment in local optima, particularly when grappling with complex optimization scenarios.

2.4.2. Overview Particle Swarm Optimization

PSO, a more recent addition to evolutionary computation techniques, was conceived by Eberhart and Kennedy [14]. 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, as well as 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. Nonetheless, PSO shares similar drawbacks to GA, including issues with convergence speed and robustness.

2.4.3. The proposed application PSO-GA for Objective function

The core concept of the hybrid GA-PSO model is to execute fitness assessments for each member of the current generation [16], [19]. Following these evaluations, individuals are chosen through the roulette wheel technique based on their fitness levels to engage in the crossover process. Here, a pair of parents exchange segments of their genetic code to conceive two offspring, which then become part of the next generation's population.

However, diverging from the conventional crossover process that can sometimes cause abrupt shifts in the direction of the search due to the exchange of genetic material, the hybrid approach introduces a novel twist. Within this pairing, the fittest individual is nominated as the global best (gbest) while the other assumes the role of the personal best (pbest) [17]. This approach means that only one parent undergoes the significant transformation inspired by the Particle Swarm Optimization (PSO) technique. Such a method is anticipated to facilitate a more thorough exploration of the search space by the hybrid algorithm.

Moreover, this PSO-inspired adjustment is selectively applied—not throughout the entire crossover period, but rather starting at a random 50% of the population at the initial phase and then progressively decreasing to just 5% over the course of the algorithm's runtime [18]. This strategy ensures a balanced and strategic search process, aiming to harness the strengths of both GA and PSO methods.

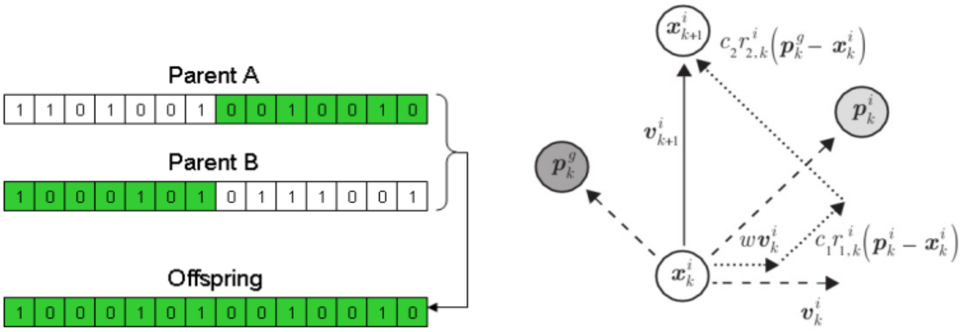

Figure 6. *(a) Crossover operation in GA* *(b) Velocity and position update in PSO*

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{11}$$

$$v_i^{k+1} = v_i^k + c_1.rand(x_i^k - pb) + c_2.rand(x_i^k - gb) \tag{12}$$

The generation of the next stage is executed through two algorithms, GA and PSO, as presented in Figure 6. Thus, the generation of a fresh populace within the Genetic Algorithm (GA) will be directed by the principles of PSO, with an initial likelihood of 50%, as per the proposition. During the algorithm's operation [17], the proportion of randomly selected progenitors undergoing this process will gradually decrease from 50% to 5%, as dictated by the prescribed formula (13).

$$rand_{down} = \frac{(0.5-0.05)}{\max(iter)}(iter) \tag{13}$$

A detailed flowchart of the proposed hybrid GA-PSO algorithm application for reconfiguration with the operating cost optimization function and taking into account the power outage cost is shown in Figure 7.

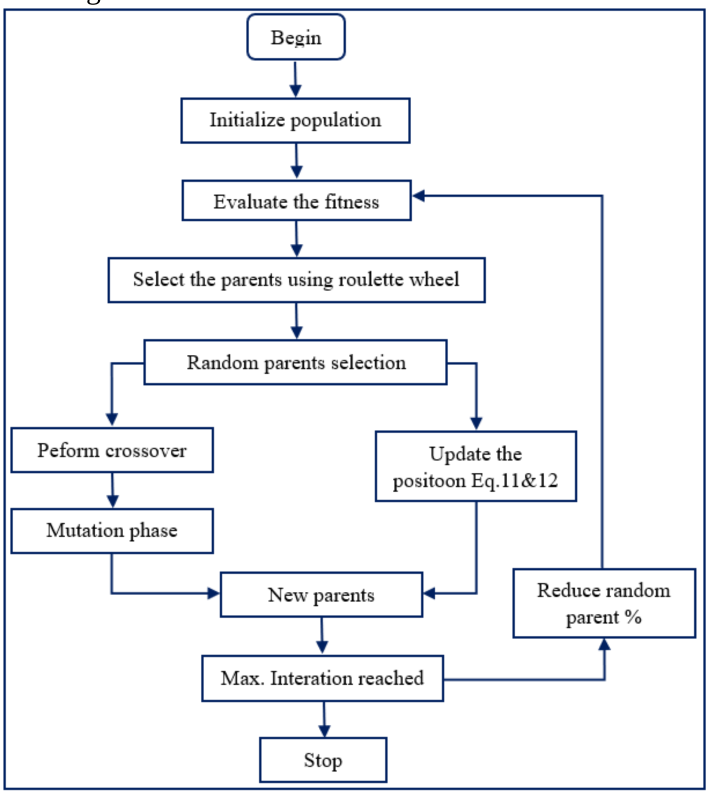

Figure 7. *Flowchart of the proposed hybrid GA-PSO for Objective function*

3. Simulation and results

The investigation includes scenarios for operational and power outage costs within the electrical network over two distinct periods: one during the dry season and another throughout the rainy season. It is hypothesized that during the dry season, the frequency of faults and the associated repair durations on the distribution lines remain consistent. In contrast, during the rainy season, these parameters are expected to vary. The objective is to determine the minimum costs associated with operation and power outages, as delineated in the objective function (10). In the standard operational mode, the electricity is priced at \$0.1 per unit (C_0), while during outages, the compensation rate is set at \$0.5 per unit (C_1).

3.1. The parameters of distribution network

The standard in [20] of IEEE distribution network includes 33 nodes as shown in Figure 8, for testing two algorithms, with 32 load nodes, and 1 nodes source, a voltage of 22.8kV, total load capacity of 3.72 MW. The initial opening switches are S33, S34, S35, S36, and S37 as shown in Figure 8 and the load graph of the network is shown in Table 1 with 8 time steps on a day and time tj = 3. To check the accuracy of the optimization algorithm in the PSO - GA field, there are three network operation cases.

Scenario 1: Involves the network functioning in a manner where the primary goal is minimizing the network's operational expenses, utilizing the PSO-GA algorithm, without taking into consideration the costs associated with power outages or the priority factor of the objective function. In this scenario, the focus is solely on achieving the least possible operational cost within the objective function.

$$COST = min\left\{\left[C_0\sum_{j=1}^{24}\Delta P_j t_j\right]\cdot 180 + 0\cdot C_1\sum_{i=1}^{n}P_i\lambda_{sci}T_{sci}\right\} \tag{14}$$

The network operating cost is:

$$COST = min\left\{\left[C_0\sum_{j=1}^{24}\Delta P_j t_j\right]\cdot 180\right\} \tag{15}$$

Scenario 2: During the dry season, the power network functions with uniform fault intensity across all lines and identical repair times, focus on an objective function where the priority factor $\alpha_1 = \alpha_2 = 1$.

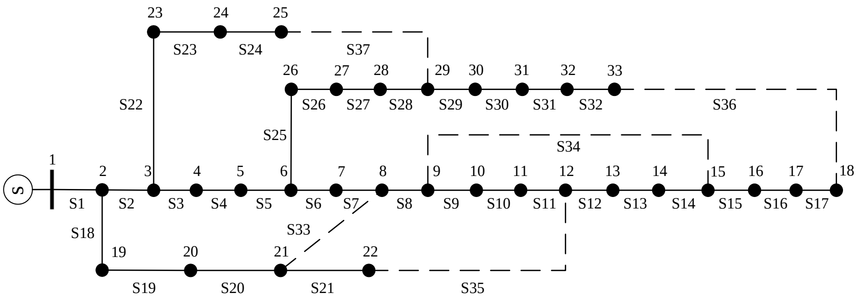

Figure 8. *Distribution network IEEE – 33 bus*

Table 1. *Load factor at the nodes in a day*

Node	**Load graph in a day**							
	0– 3	**3 – 6**	**6– 9**	**9– 12**	**12– 15**	**15– 18**	**18– 21**	**21– 24**
0	0	0	0	0	0	0	0	0
1-32	0.6	0.8	1	1.1	1	1	0.6	0.5

The power network is considered in the following three cases:

Case 1: Study of the original 33-bus Distribution System in the sunny season, assuming that the frequency of line faults in branches is the same at λ = 0.1 times/season, and the repair time for the lines in the branches is equal at t = 10 hours, with all loads being equally important. The operating cost of the electrical network is F = $306,190.

Case 2: Study of the original 33-bus Distribution System in the rainy season, assuming that the frequency of line faults in branches 8 – 21, 15 – 9, 22 – 12 is the same at λ = 0.2 times/season, the frequency of line faults in branch 6 – 26 is λ = 0.3 times/season, in branch 3 – 23 is λ = 0.4 times/season, in branch 2 – 19 is λ = 0.5 times/season, and in the remaining branches is the same at λ = 0.1 times/season. The repair time for the lines in the branches is equal at t = 10 hours, with all loads being equally important. The operating cost of the electrical network is F = $354,750.

The proposed method is simulated on the power grid model shown in Figure 9, conducted with two scenarios: the dry season and the rainy season.

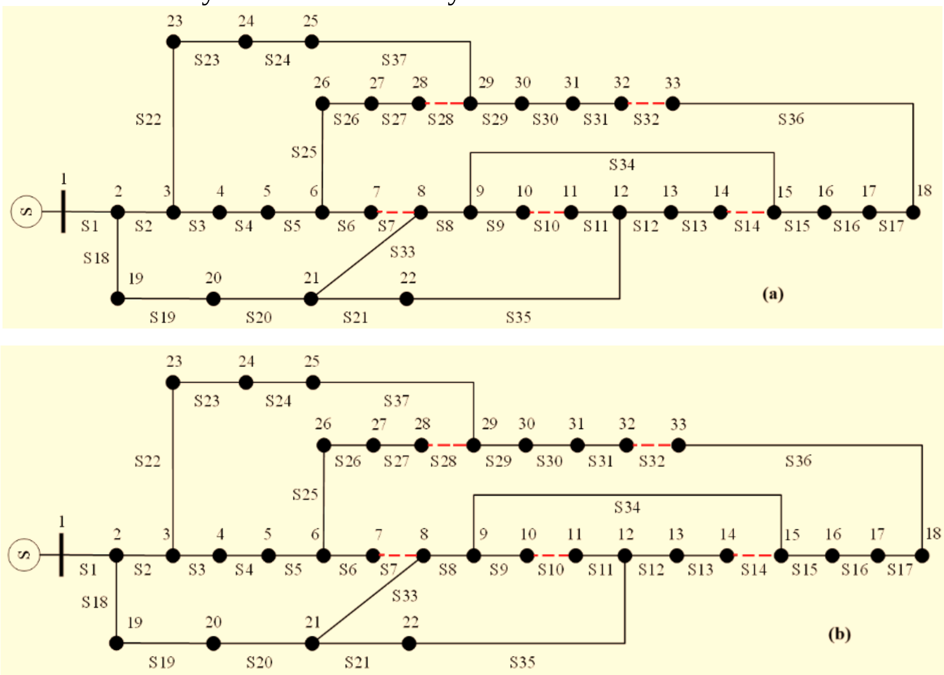

Figure 9. *The 33-bus distribution network after reconfiguration during the sunny (a) and rainy (b) season*

Simulation results were performed using the same three scenarios for a 33-node sample network, and the results are shown in Table 2.

Table 2. *Comparison of pre and post-configuration results*

	Cost according to objective function ($/season)	Opening switches	Power loss in a season (Kwh)
Initial	Scenario 1: 306.190 Scenario 2: 354.750	S_{33},S_{34},S_{35},S_{36},S_{37}	900.320
Scenario 1	228,981	S_7, S_{10},S_{14},S_{28},S_{32}	606.758
Scenario 2	295,421	S_{10},$S_{14}$$S_{28}$,$S_{33}$,$S_{36}$	

Table 2 indicates that, after reconfiguring the electrical network, the operational and outage costs in cases 1 and 2 decreased by 14.5%, and the power loss also reduced by nearly 20%. Therefore, after reconfiguration, it is possible to reduce operational costs and enhance the reliability of the electrical network. The calculated results are compared with those obtained from the GSA [20], as presented in Table 3.

Table 3. *Comparison of results after reconfiguring the 33-bus electrical network with GSA* [20]

DRN	Cost according to objective function ($/season)	Opening switches	Power loss in a season (Kwh)	Integrations
Scenario 1				
PSO-GA	228,740	S7, S10, S14, S28, S32	607.770	12
GSA [20]	228,740	S7, S10, S14, S28, S32	607.770	15
Scenario 2				
PSO-GA	295,134	S7, S10, S14, S28, S32	607.770	12
GSA [20]	310,390	S10, S14, S28, S33, S36	654.290	15

In Table 3, it is observed that after reconfiguring the 33-bus network in case 1, the proposed method and GSA [20] have the same open switches. The objective function and power losses of the proposed method are equal to those of GSA [20]. In case 2, regarding the configuration, the two methods differ in open switches: the proposed method (S7, S32) and GSA [20] (S33, S36), while the objective function and power losses of the proposed method are smaller compared to GSA [20]. Thus, it can be seen that the proposed method has a better configuration than GSA [20], as the proposed method calculates based on average power, hence the configuration in both cases does not change, whereas GSA [20] calculates based on peak power, leading to a change in configuration.

4. Conclusions

The trial runs have demonstrated the effective application of the PSO-GA algorithm in addressing the distribution network reconfiguration challenge. By conducting tests on systems with 33 nodes across two different operational scenarios that vary in outage rates, the impact on the cost function was assessed. The computational findings confirm that the algorithm yields an optimal reconfiguration scheme that guarantees the most economical operation costs. Consequently, this approach serves as a promising and efficient strategy for tackling the reconfiguration issues of distribution networks, with a particular focus on power supply considerations during network operations, and holds promise for practical implementation.

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