Optimization of Network Reconfiguration and Distributed Generation Allocation with Nonlinear Load Models Using Growth Optimizer

Thuan Thanh Nguyen

Faculty of Electrical Engineering Technology, Industrial University of Ho Chi Minh City, No. 12 Nguyen Van Bao, Hanh Thong Ward, Ho Chi Minh City, Viet Nam, e-mail: nguyenthanhthuan@iuh.edu.vn

Abstract: The distribution network (DN) has large-scale and operates at low-voltage level. This causes a high-power loss and voltage drop that negatively affects different load types in the DN. This paper optimizes the network reconfiguration along with distributed generation allocation (REC-DGA) in the DN with different load models to minimize power loss of the DN and consider maintaining the radial-topology, the grid and distributed generation power limits and improving the voltage and current profiles. The five load models, which have voltage-dependent power characteristics, are used to evaluate the effects of the simultaneous REC-DGA solution. A new metaheuristic algorithm namely growth optimizer (GO) is adapted for searching the optimal solution for the simultaneous REC-DGA. The performance of GO is also compared to particle-swarm-optimization (PSO) and genetic-algorithm (GA). The results evaluated on the 33-node DN show that the optimal simultaneous REC-DGA helps to dramatically reduce power loss. The power loss reduction compared to the initial configuration of the cases of constant power, industrial, residential, commercial, and mixed loads is respectively 74.98%, 73.89%, 72.08%, 70.83% and 72.41%. Furthermore, the optimal REC-DGA also helps enhance the voltage, current profiles, and the power of load demand in the DN. In comparison with PSO and GA, GO achieves the better performance than PSO and GA and the better results compared with previous methods.

Keywords: distribution network; network reconfiguration; distributed generation allocation; power loss; growth optimizer

1 Introduction

Distribution network (DN) is one of the most complex parts of the power system due to the large number of loads and feeders. However, power loss on the DN accounts for a significant portion, about 10-13% of the total system generation capacity [1]. The high-power loss of the DN means that the allowable voltage configuration is not guaranteed in operation of the DN. Meanwhile, there are many loads in the DN such as industrial, residential, and commercial loads that have voltage-dependent power characteristics. This directly affects the operating ability of the loads. To overcome these difficulties, network reconfiguration (REC) combined with the installation of distributed generation (DG) is an effective solution to this problem. REC is the process of selecting the radial network structure of the DN through the opening and closing of existing electrical switches on the DN. The DG is types of small power sources that are usually directly connected to the DN to generate active power, reactive power, or both active and reactive power [2]. In Vietnam, in recent years, the output capacity from DG using photovoltaic (PV) has grown strongly and reached 16.7 GW, accounting for 2% of the total global installed PV capacity [3]. In the past decade, the PV DG capacity has been installed up to 20% of the total new installed capacity coming from DG [4]. This is an opportunity to improve the efficiency of power supply but also a challenge for optimizing the location and capacity of them on the DN.

In recent years, many studies have been conducted on the REC-DGA problem. In these studies, REC-DGA is mainly used to improve technical indicators in the DNs. In [5], the power loss of the DN is minimized by the REC-DGA. In [6], the REC-DGA is considered to maximize voltage stability index and minimize power loss. In [7], power loss and load ability are optimized by the REC-DGA. In [8], the REC-DGA is solved for improving voltage stability and minimizing power loss in the DN considering probabilistic load flow. The REC-DGA for optimizing of power loss, operational cost and voltage stability of the DN is carried in [9]. However, the above studies mainly use the constant power load model or extend the constant power load levels for the REC-DGA problem. There are only a few studies to consider different load models, but they are mainly used for the DGA or REC problem separately without combining both of these problems. For example, in [2], types of loads including constant impedance, constant power, and constant current are considered in the process of optimizing DG installation to reduce power losses. In [10], the optimal DG and capacitor installation problem on the DN is considered to optimize power loss, voltage profile, and system stability, wherein the types of loads include constant power, industrial, residential, commercial, constant current and constant impedance loads are considered. In [11], the REC problem with the impact of constant power, industrial, residential, and commercial load types to reduce power losses is considered. From a methodological perspective, in recent years, optimization techniques have played a central role in improving the performance and intelligence of both technical and non-technical systems [12]. Recent studies have demonstrated the diversity of optimization applications in various engineering problems, such as optimizing diesel locomotive operating parameters to reduce fuel consumption [13], optimizing expert knowledge bases [14] and learning rates [15] in machine learning, optimizing nonlinear servo control systems [16], and optimizing the applied plastic loads in reinforced concrete structures in construction [17]. Optimization is not only a theoretical tool but also a practical solution that enables multi-disciplinary engineering systems to operate more intelligently and efficiently. For the REC-DGA problem, it is a constrained optimization problem that has so far have been primarily solved using optimization methods based on metaheuristic algorithms such as equilibrium-optimization (EO) [6], modified particle-swarm-optimization MPSO [18], elitist-jaya (IEJAYA) [7], three-dimensional-group-search-optimization (3D-GSO) [5] and fireworks-algorithm FWA [19]. Nowadays, there are many new algorithms being developed. Their effectiveness is mainly evaluated on standard mathematical functions. Therefore, the question is that it is necessary to apply them for technical problems like the REC-DGA problem to expand application possibilities as well as diversify solving methods for technical problems that should be encouraged for implementation.

Although there are many studies related to the REC-DGA problem, most previous works use the constant power load model that is an unrealistic mode in operation of the DN. In addition, in the context of strong development of DG using PV in Vietnam, consideration of this type of DG when connecting to the DN needs to be done. In terms of solving methods, many studies use optimization algorithms for the REC-DGA problem. However, there is no effective one for every problem [20]. Searching and applying new methods for the REC-DGA problems needs to be continuously carried out. In the context of strong development in the field of optimization, more new algorithms are being developed, i.e. growth-optimizer (GO). GO is a recent algorithm taken metaphor from the learning and reflection of people in society [21]. GO has been shown its high performance for benchmark functions and two engineering problems in [21] and optimal soft open point placement and open switch position [22]. However, the efficiency of GO for the REC-DGA also needs to be carried out.

In this paper, five load model types are considered including constant power, industrial, residential, commercial and mixed loads. The power of these types of loads has a nonlinear relationship with the voltage amplitude applied to them. To perform load flow analysis for the DN with these types of loads, the Newton-Raphson method is adapted to calculate node voltages, branch power, feeder power and power loss in the DN. The GO optimization algorithm is used to determine the open switches, location and installed capacity of the DGs in the considered cases. The goal of optimizing the radial configuration of DN and DG allocation is to reduce power loss and consider constraints such as the voltage profile, overload in the DN and the DG power returning to the feeders. The problem of optimizing the radial configuration, location, and installed capacity of DG is carried out on the 33-node DN. The ability of the GO method for the REC-DGA problem considering load types is evaluated through comparison results with the well-known algorithms consisting of particle-swarm-optimization (PSO) and genetic-algorithm (GA), which in turn takes ideas from the behavior of birds in the process of searching for food and from the evolutionary process of organisms in nature. In addition, the results of GO are also compared with those of the previous studies. The paper's main contributions are summarized as follows:

(i) Propose solution of power loss reduction relied on REC-DGA considering nonlinear load models.

(ii) Detail steps of GO for the simultaneous REC-DGA problem considering different nonlinear load models

(iii) It is demonstrated that the simultaneous REC-DGA based on GO algorithm does not only reduce power loss but also enhances the power of load demand for nonlinear load models.

(iv) The compared results with PSO and GA as well as the previous methods and the statistical analysis have shown that GO is an effective method for the optimal simultaneous REC-DGA considering different nonlinear load models.

2 Problem of Network Reconfiguration and DG Allocation considering Nonlinear Load Models

2.1 The Problem of REC-DGA for Minimizing Power Loss

Power loss is the most important indicator during DN operation. Thus, in this work, power loss minimization is considered optimal goal in the REC-DGA process. Let X denote the decision vector of the REC–DGA problem that consists set of open switches, DG locations and its active power. The power-loss objective is defined as follows:

$$Minimize\ P_{loss}\ (X) = \sum_{i=1}^{N_{br}} \mu_i . \Delta P_i \tag{1}$$

Wherein, X is set of open switches, location and power DGs. P_{loss} is power loss of the DN. ΔP_i is power loss of branch i. N_{br} is number of branches. $\mu_i \in \{0, 1\}$ is the status of branch i that is 1 for closed branches and 0 for open ones.

The optimization of REC-DGA is subject to the following constraints:

i) Constraint of the radial-topology structure [23]:

$$|det\ (A)| = 1 \tag{2}$$

Where, $det\ (A)$ is determinant of connected matrix of the DN, wherein $A(i, j)$ is 1 or -1 if branch i connected from/to the node j, otherwise $A(i, j)$ is 0.

ii) Constraint of power of DGs: Power of DGs should be in their capacity limit:

$$P_{DG,i} \leq P_{DG,i,rate} \quad ; i = 1, \dots , N_{DG} \tag{3}$$

iii) Constraint of voltage profile: The voltage amplitudes in the DN should be in the allowed range:

$$V_L \le V_j \le V_U \; ; j = 1, \dots, N_b \tag{4}$$

Wherein, V_j is the voltage amplitude of node j. N_b is number of buses. V_L and V_U is the allowed voltage limits that are often chosen to $0.95\ pu$ and $1.05\ pu$.

iv) Constraint of current profile: The branch currents should be in the allowed range:

$$KI_i \le 1 \quad ; i = 1, \dots, N_{br} \tag{5}$$

Wherein, KI_i is load-carrying coefficient of branch i that is defined by ratio of current flowing on branch i and its rate value.

Wherein, $P_{DG,i}$ and $P_{DG,i,rate}$ current and rated power of DG i.

v) Constraint of grid power: To increase independence and avoid affecting the grid, the generating capacity of DGs is not returned to the grid. It is ensured by the follows equation:

$$P_{grid} \ \ge 0 \tag{6}$$

Wherein, P_{grid} is the power supplied from the grid to the DN.

2.2 Load Models

Since the load characteristics significantly affect the power flow and loss evaluation, different nonlinear load models are considered. This section introduces the nonlinear load representations employed in the optimization process. Generally, the load demand is assumed as constant for load-flow analysis. However, in reality loads such as industrial, residential and commercial are dependent on voltage. Thus, in this work, the load models are represented in terms of their power as follows [10], [24]:

$$\begin{cases} P_i^{sch} = P_{0i}^{sch} \cdot \left(\frac{|V_i|}{|V_{0i}|}\right)^{\alpha} \\ Q_i^{sch} = Q_{0i}^{sch} \cdot \left(\frac{|V_i|}{|V_{0i}|}\right)^{\beta} \end{cases} \tag{7}$$

Wherein, $\left[P_i^{sch}, Q_i^{sch}\right]$ and $\left[P_{0i}^{sch}, Q_{0i}^{sch}\right]$ are respectively the real demand and schedule demand at the nominal condition. V_i and V_{0i} are the real and nominal voltages at bus i. α and β are exponential coefficient for load types. The value of α and β for load types are presented in Table 1 [10]:

Table 1

Exponent coefficients for load types

Load type	Constant power	Industrial	Residential	Commercial
α	0	0.18	0.92	1.51
β	0	6.0	4.04	3.4

2.3 Load Flow for Different Nonlinear Load Models

To accurately evaluate the objective function of the REC-DGA problem under nonlinear load conditions, this section describes the power flow calculation approach developed for DN with nonlinear loads.

Because of the voltage dependence of load, each node's load needs to be updated during the load flow process. Therefore, the steps to perform load flow for PQ buses based on the Newton-Raphson method are adjusted as follows:

Step 1: Generate node voltage V_i

Step 2: Calculate the schedule power at node i using (7)

Step 3: Calculate the power at node i

$$\begin{cases} P_i = \sum_{k=1}^{N_b} |V_i V_k Y_{ik}| \cos\left(\delta_i - \delta_k - \theta_{ik}\right) \\ Q_i = \sum_{k=1}^{N_b} |V_i V_k Y_{ik}| \sin\left(\delta_i - \delta_k - \theta_{ik}\right) \end{cases} \tag{8}$$

Where P_i and Q_i are the active and reactive power at node i. V_i, V_k and δ_i, δ_k are voltage amplitude and angle of node i and k respectively. Y_{ik} and θ_{ik} are the mutual admittance amplitude and angle respectively.

Step 4: Calculate the change power

$$\begin{cases} \Delta P_i = P_i^{sch} - P_i \\ \Delta \mathrm{Q}_i = Q_i^{sch} - Q_i \end{cases} \tag{9}$$

And determine the maximum change power ΔP_{max} and ΔQ_{max}. If ΔP_{max} and ΔQ_{max} are less than the allowed accuracy, line flows are calculated. Otherwise, the below steps are executed.

Step 5: Calculate the Jacobian matrix's elements H, N, M, L:

The off-diagonal and diagonal elements of H, N, M, L matrixes is respectively determined by the equation (10), (11), (12) and (13):

$$\begin{cases} \frac{\partial P_i}{\partial \delta_k} = |V_i V_k Y_{ik}| \sin(\delta_i - \delta_k - \theta_{ik})\,; i \neq k \\ \frac{\partial P_i}{\partial \delta_i} = -\sum_{\substack{k=1 \\ k \neq i}}^{n} |V_i V_k Y_{ik}| \sin\left(\delta_i - \delta_k - \theta_{ik}\right) \end{cases} \tag{10}$$

$$\begin{cases} \frac{\partial P_i}{\partial |V_k|} = |V_i Y_{ik}| \cos(\delta_i - \delta_k - \theta_{ik})\,;\ i \neq k \\ \frac{\partial P_i}{\partial |V_i|} = 2|V_i Y_{ii}| \cos(\theta_{ii}) + \sum_{\substack{k=1 \\ k \neq i}}^{n} |V_k Y_{ik}| \sin\left(\delta_i - \delta_k - \theta_{ik}\right) \end{cases} \tag{11}$$

$$\begin{cases} \frac{\partial Q_i}{\partial \delta_k} = -|V_i V_k Y_{ik}| \cos(\delta_i - \delta_k - \theta_{ik})\,; i \neq k \\ \frac{\partial Q_i}{\partial \delta_i} = -\sum_{\substack{k=1 \\ k \neq i}}^{n} |V_i V_k Y_{ik}| \cos\left(\delta_i - \delta_k - \theta_{ik}\right) \end{cases} \tag{12}$$

$$\begin{cases} \frac{\partial Q_i}{\partial |V_k|} = |V_i Y_{ik}| \sin(\delta_i - \delta_k - \theta_{ik})\ ;\ i \neq k \\ \frac{\partial Q_i}{\partial |V_i|} = -2|V_i Y_{ii}| \sin(\theta_{ii}) + \sum_{\substack{k=1 \\ k\neq i}}^{n} |V_k Y_{ik}| \sin(\delta_i - \delta_k - \theta_{ik}) \end{cases} \tag{13}$$

Step 6: Solve the equation:

$$\begin{bmatrix} H & N \\ M & L \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta|V| \end{bmatrix} = \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} \tag{14}$$

Step 7: Update the node volatge:

$$\begin{cases} \delta_i = \delta_i + \Delta\delta_i \\ |V_i| = |V_i| + \Delta|V_i| \end{cases} \tag{15}$$

The process comes back to step 2 for continuing until ΔP_{max} and ΔQ_{max} are less than the allowed accuracy (ε). The flowchart of the Newton-Raphson method for PQ buses considering the load models is shown in Figure 1.

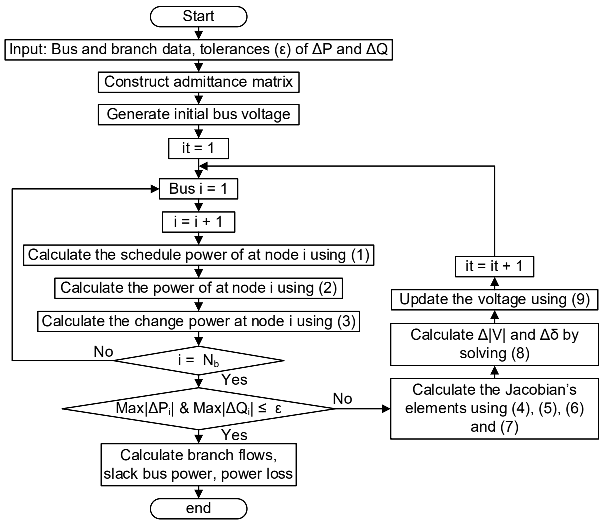


Figure 1

The Newton-Raphson method for load flow considering the load models

3 Optimization of REC-DGA using the GO Algorithm

In this study, the optimization problem is formulated to minimize the active power loss of the DN while satisfying operational constraints such as radial topology structure, voltage and current limits, and power exchange limits with the main grid.

The decision variables include the locations of open switches, as well as the placement and power of DGs to be installed. To obtain the optimal solution for the REC-DGA problem, each individual represents a configuration scheme of the network along with the DG location and power. The process of updating the population through learning and reflection mechanisms enables the algorithm to gradually converge toward the global optimum. The decision variables in each solution are described as follows:

$$\mathrm{X} = [S_1, S_2, \dots, S_{nsw}, L_1, L_2, \dots, L_{ndg}, P_1, P_2, \dots, P_{ndg}] \tag{16}$$

Where, $\{S_1, S_2, \dots, S_{nsw}\}$ displays open switch positions. $\{L_1, L_2 \dots, L_{ndg}\}$ and $\{P_1, P_2, \dots, P_{ndg}\}$ present the location and capacity of DGs.

The process of mapping each decision-variable solution of the GO algorithm for the REC-DGA problem model is summarized as follows:

(i) From each decision-variable solution X generated during the initialization and updated through the learning and reflection mechanisms of the GO algorithm, the sub-vector $[S_1, S_2, \dots, S_{nsw}]$ is updated into the branch data of the DN by removing the branches containing $S_1, S_2, \dots, S_{nsw}$ from the branch parameters of the DN.

(ii) The remaining branches of the DN are then checked for the radiality condition according to Eq. (2).

(iii) If the radial-topology condition is not satisfied, a very large value is assigned to the fitness function of solution X. Conversely, if the radiality condition is satisfied, the control-variable subvector $[L_1, L_2, \dots, L_{ndg}, P_1, P_2, \dots, P_{ndg}]$ is updated into the bus data of the DN. Then, the load flow procedure described in Section 2.3 is executed to obtain the bus voltages, branch currents, and power loss of the DN, and the fitness value of solution X is calculated based on Eq. (17).

$$\mathrm{F(X)} = P_{loss}\,(X) + k \cdot \Big[\sum_{j=1}^{N_b} \Big(max(V_j - V_U, 0) + max(V_L - V_j, 0)\Big) + \sum_{i=1}^{N_{br}} max(KI_i - 1{,}0) + |min(P_{grid}, 0)|\Big] \tag{17}$$

Where, F_i is the fitness value of solution i. k is the penalty coefficient.

(iv) These steps are carried out for each decision-variable solution of the GO algorithm. The fitness values of the decision-variable individuals help guide the updating and evolution process of the GO population.

The process of initializing and updating GO individuals for the REC-DGA problem is performed according to the following steps:

Step 1: Generate random solutions the REC-DGA

Each solution in the population is created as follows:

$$X_{i,j} = X_{L,j} + r_1 \cdot (X_{H,j} - X_{L,j}) \tag{18}$$

Where, $X_{i,j}$ is the variable j $(j = 1, \dots, D)$ of the solution $(i = 1, \dots, N)$. r_1 is the random number in [0, 1]. $[X_{L,j}, X_{H,j}]$ is the limit of the variable j. N and D are the population size and dimension.

Because the open switch position and DG installation position are branches and nodes on the DN, respectively, these variables need to be adjusted after the initialization process as follows:

$$\begin{cases} S_{i,j} = round(S_{i,j}); j = 1,2, \dots, nsw \\ L_{i,j} = round(L_{i,j}); j = 1,2, \dots, ndg \end{cases} \tag{19}$$

Based on the information of each adjusted solution, the DN parameters are updated, and the fitness function value of each solution is calculated. Based on the fitness function value, the global best solution X_{gbest} is determined.

Step 2: Update the solution based on the learning phase

In this step, individuals are updated based on interactions with other individuals in the population. Based on the value of the fitness function of the solutions, the current best solution of the population (X_{best}) is determined. The next P_1 good solutions are classified as better individuals (X_{bet}) and the remaining solutions are considered bad individuals (S_{wor}). After being classified, the spaces between them are determined as follows:

$$\begin{cases} g_1 = X_{best} - X_{bet,b} \\ g_2 = X_{best} - X_{wor,w} \\ g_3 = X_{bet,b} - X_{wor,w} \\ g_4 = X_{r1} - X_{r2} \end{cases} \tag{20}$$

Where, X_{r1} and X_{r2} are random selected individuals. $X_{bet,b}$ and $X_{wor,w}$ are respectively solutions selected randomly in the better and worse pools.

The influence of these gaps on the update process of solutions is defined as follows:

$$L_k = \frac{\|D_k\|}{\|D_1 + D_2 + D_3 + D_4\|}; k = 1, 2, 3, 4 \tag{21}$$

Where, L_k is the learning level of each solution that is effected by the gap k.

Additionally, in GO each solution has a different learning level. If the solution is at a good level, it will learn less from other solutions. On the contrary, if it is at bad quality, it will have to learn more information from other individuals. This is described mathematically as follows:

$$S_i = \frac{F_i}{F_{worst}} \tag{22}$$

Where, S_i is the learning factor of solution i. F_{worst} is the fitness value of the worst solution.

Finally, the new solution is generated as follows:

$$\mathrm{X}_i^{new} = X_i + S_i \cdot [L_1 \cdot g_1 + L_2 \cdot g_2 + L_3 \cdot g_3 + L_4 \cdot g_4] \tag{23}$$

Each newly created solution is checked its bounds to ensure it is all within the allowed limits and adjusted the information according to (19). Then, the fitness function value of each solution is calculated. Based on the fitness function value, the current solutions are updated according to the selection principle as follows:

$$X_i = \begin{cases} \mathrm{X}_i^{new}; & if\ F_i^{new} < F_i \\ \begin{cases} \mathrm{X}_i^{new}; \ if\ r_2 < P_2 \\ X_i; \quad ortherwise \end{cases} & ortherwise \end{cases} \tag{24}$$

Where, P_2 indicates the knowledge memory probability of solution X_i.

Then, the global optimal solution is also updated as follows:

$$X_{gbest} = \begin{cases} X_i \quad ;\ if\ F_i < F_{gbest} \\ X_{gbest};\ \ ortherwise \end{cases} \tag{25}$$

Step 3: Update the solution based on the reflection phase

In this process, each individual can be updated from information of better individuals while their good information can be retained. Based on this principle, each solution is updated as follows:

$$X_{i,j}^{new} = \begin{cases} \begin{cases} X_{L,j} + r_4 \cdot (X_{H,j} - X_{L,j});\ if\ r_3 < RF \\ X_{i,j} + r_5 \cdot (X_{b,j} - X_{i,j}) \quad ;\ orthewise \end{cases} & ;\quad if\ r_2 < P_3 \\ X_{i,j} & ;\ ortherwise \end{cases} \tag{26}$$

Where, r_2 to r_5 are random numbers. P_3 is the reflection coefficient. $X_{b,j}$ is variable of the better or best solution. RF is the reduction factor determined as follows:

$$RF = 0.01 + 0.99 \cdot (it/maxit) \tag{27}$$

Where, it and $maxit$ are the current and maximum number of iterations.

Each newly created solution is checked its bounds to ensure it is all within the allowed limits and adjusted the information according to (19). Then, the fitness function value of each solution is calculated. Based on the fitness function value, the current solutions are updated according to the selection principle in (24) and the global best solution is updated one gain by (25).

Step 4: Stop updating the solution

The process of finding new solutions and updating the current solutions of GO from step 2 to step 3 is done in $maxit$ iterations. At the end of the above iterative process, the globally optimal solution is considered the solution of the REC-DGA problem. The flowchart of GO for the REC-DGA problem considering the load models is shown in Figure 2.

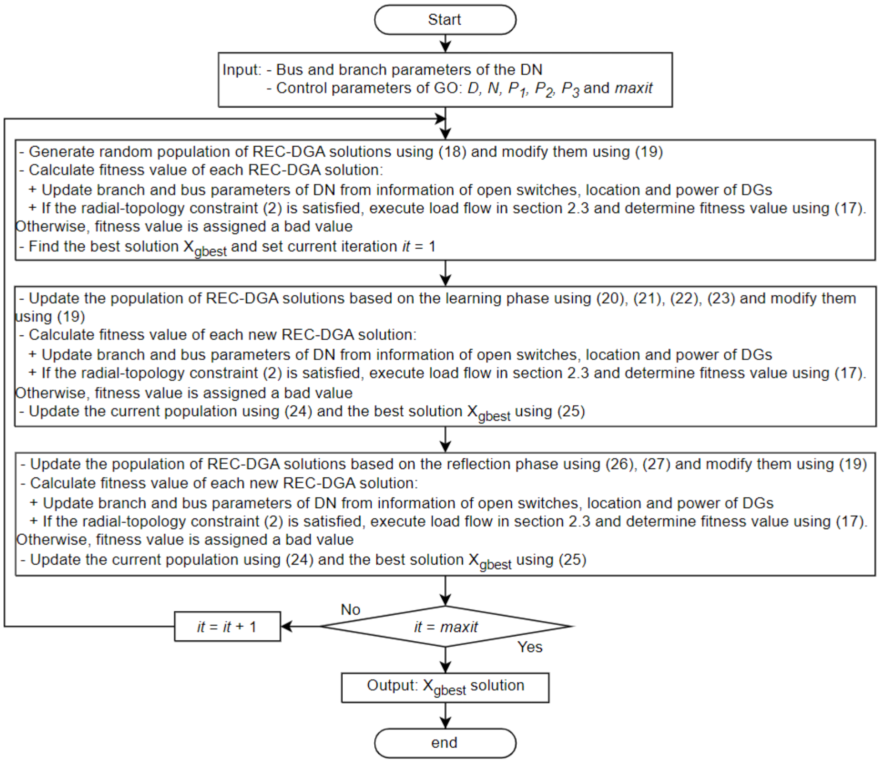


Figure 2

The GO method for the REC-DGA problem considering the load models

4 Results and Discussion

The REC-DGA problem model and proposed method based on GO is applied to find optimal open switches as well as location and power of DGs on the DN shown in Figure 3 [25]. The branches' rated current is 255 A [23]. The number of DGs be installed on this system is limited to 3 with maximum capacity is 2MW for each.

To consider the influence of load model types as described in section 2.1 and section 2.2 on REC-DGA results, at each load nodes of the DN, the five cases consisting of constant power load (CON), industrial load (IND), residential load (RES), commercial load (COM) and mixed load (MIX) are considered. For the MIX load, the proportion of industrial, residential and commercial loads at each node is determined by the following equation:

$$\begin{cases} P_i^{sch} = P_{0i}^{sch} \cdot \left(0.4 \cdot \left(\frac{|V_i|}{|V_{0i}|}\right)^{0.18} + 0.3 \cdot \left(\frac{|V_i|}{|V_{0i}|}\right)^{0.92} + 0.3 \cdot \left(\frac{|V_i|}{|V_{0i}|}\right)^{1.51}\right) \\ Q_i^{sch} = Q_{0i}^{sch} \cdot \left(0.4 \cdot \left(\frac{|V_i|}{|V_{0i}|}\right)^{6} + 0.3 \cdot \left(\frac{|V_i|}{|V_{0i}|}\right)^{4.04} + 0.3 \cdot \left(\frac{|V_i|}{|V_{0i}|}\right)^{3.4}\right) \end{cases} \tag{28}$$

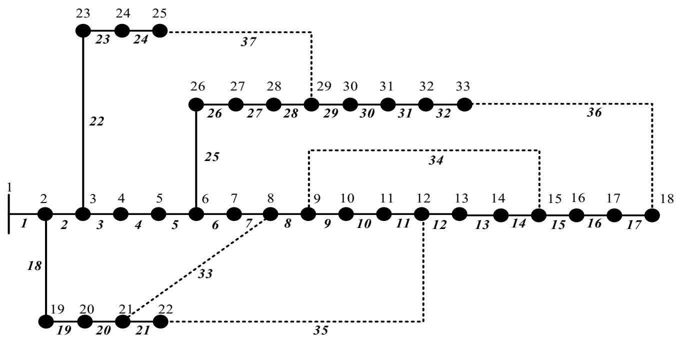
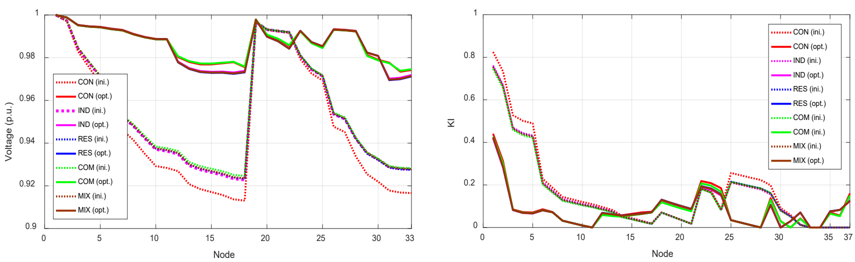


Figure 3
The 33-node DN

To find the optimal solution for the REC-DGA problem considering the load types using GO, the number of decision variables is set to 11, with the first five representing the locations of open switches, the next three corresponding to the installation positions of the three DG units, and the last three representing the respective capacities of these DGs. For GO algorithm, the population size and the maximum number of iterations are chosen to be 30 and 500, respectively. Other control parameters GO include P_1, P_2 and P_3 are chosen to be 5, 0.001 and 0.3, respectively [21]. In addition, to compare the effectiveness of the GO algorithm for the REC-DGA problem, two famous algorithms including PSO and GA are also applied to find the optimal solution for cases of the problem. While GO is developed based on the idea of human adaptation in society, PSO is an algorithm based on the behavior of birds in the process of searching for food, and GA is inspired by the evolutionary process of organisms in nature. The population size of PSO and GA is chosen to be 60 because both algorithms only update the population once in each iteration. The specific control parameters of PSO include velocity constants C_1 and C_2 chosen to be 2 [26] while the crossover and mutation rates of GA are chosen to be 0.5 and 0.2 [27]. The GO algorithm applied to the REC-DGA problem is implemented in MATLAB software wherein the load flow program with different load models is developed based on the Matpower tool [28] to obtain the power loss, voltage and current profiles for calculating the fitness function value of each decision variable solution of GO. The proposed method is run on personal computers with Windows 11 (64-bit), Intel Core i7-1360P 2.2 GHz, 16 GB RAM.

The results of implementing REC-DGA for different load types are presented in Table 2. For the CON load, the total load power before and after implementing REC-DGA does not change. After installing DG at nodes of{17, 7 and 25} with power of {0.75296, 0.956946 and 1.27957 MW} respectively combined with open switches of {33-34-11-31-28}, P_{loss} reduction of the DN is 151.9674 kW corresponding to the reduction of 74.98% compared to that of the initial DN. The smallest voltage amplitude (V_{min}) is improved by 6.60% from 0.9131 to 0.9734 pu. The highest load-carrying coefficient (KI_{max}) is also reduced by 46.58% compared to that of the original DN. The supplied power from the grid is also decreased from 3.9177 to 0.7762 MW and there is no power from the DGs returned to the grid.

For IND loads, after implementing REC-DGA, power loss is reduced by 73.89% compared to that of the original DN. The V_{min} is improved by 5.14% and the KI_{max} factor is reduced by 45.04%. Similarly, for the RES and COM loads, the benefits in term of P_{loss} reduction, V_{min} improvement and KI_{max} reduction are respectively {72.08%, 4.99% and 43.60%} for the RES load, and {70.83%, 4.83% and 42.56%} for the COM load. In the case of MIX load, after performing REC-DGA, with open switch positions of {33-34-11-30-28} and DGs placement of {0.929037 MW (at node 7), 0.818957 MW (at node 18), 1.01966 MW (at node 25)}, the power loss has decreased by 158.6091 kW to 43.7611 kW corresponding to a reduction of 72.41%. The V_{min} is increased from 0.9235 to 0.9697 pu corresponding to an increase of 5.00% and the KI_{max} is reduced by 43.85% compared to those of the original DN. Figure 4 presents the voltage and current profiles before and after performing REC-DGA for different load types, wherein the dot lines present the voltage/current profile of the initial case (ini.) and the solid lines show the voltage/current profile of the optimal case (opt.). The figure shows that for all types of loads, after performing REC-DGA, the better DN state is obtained than the initial state of the DN in terms of power loss, voltage, and current profiles. Notably, the voltage amplitudes of the nodes are all within the allowable range of [0.95, 1.05 pu] and no line overload occurs in the DN after REC-DGA.



a) Voltage profile b) Current profile

Figure 4

Comparison of voltage and current profiles with different load types before and after REC-DGA

Figure 5 shows that for voltage-dependent loads, the rated power of the loads decreases significantly, when the voltage value at the nodes does not reach the rated value. The total active load for industrial, residential, commercial, and mixed loads before implementing REC-DGA is reduced by 0.81%, 4.05%, 6.45% and 3.49% respectively compared to the constant power load, wherein the commercial load has the largest decline. After performing REC-DGA, because the load remains unchanged of the constant power load type, the load power before and after performing REC-DGA does not change compared to the original even though the system voltage indicators change. For the industrial, residential, commercial, and mixed loads, the total active load power has increased from {3.6848, 3.5645, 3.4754 and 3.5854 MW} to {3.7049, 3.6634, 3.6357 and 3.6703 MW}, respectively corresponding to an increase of {0.55%, 2.77%, 4.47% and 2.37%} compared to the original load thanks to the improvement of voltage profile. This shows that implementing REC-DGA not only reduces power loss, but the resulting technical benefits also help the load connected to the DN to operate with parameters as close to the rated value as possible.

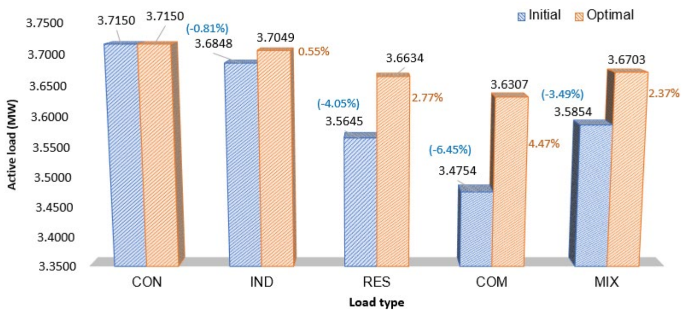


Figure 5

Comparison load demand before and after REC-DGA for the 33-node DN

The comparison results between GO, PSO and GA for different load type cases are presented in Table 3. In all cases, the open switches, the DGs'location and power found by GO gain smaller power loss compared to PSO and GA. The power loss obtained by PSO for the CON, IND, RES, COM, and MIX load types are 54.4019, 43.4870, 47.2139, 49.1772 and 45.3293 kW, respectively. These values are respectively 7.26%, 3.01%, 6.14%, 8.81% and 3.58% higher than that of GO. For GA, the power loss obtained in cases are lower than PSO, but they are still 1.44%, 0.43%, 0.30%, 0.26% and 0.12% higher than that of GO.

Table 2

The REC-DGA results for the 33-node DN with different load models

Item	CON load		IND load		RES load		COM load		MIX load	
	Initial	Optimal	Initial	Optimal	Initial	Optimal	Initial	Optimal	Initial	Optimal
Load (MW, MVAr)	3.7150, 2.3000	3.7150, 2.3000	3.6848, 1.7177	3.7049, 2.0920	3.5645, 1.8850	3.6634, 2.1565	3.4754, 1.9481	3.6307, 2.1784	3.5854, 1.8374	3.6703, 2.1371
OS	33-34-35-36- 37	33-34-11-31- 28	33-34-35-36-37	33-34-11-30-28	33-34-35-36-37	33-34-11-30-28	33-34-35-36-37	33-34-11-30-28	33-34-35-36-37	33-34-11-30-28
DG (MW) [node]	None	0.75296 (17), 0.95695 (7), 1.27957 (25)	None	1.01000 (25), 0.82796 (18), 0.92957 (7)	None	1.02672 (25), 0.93025 (7), 0.81882 (18)	None	1.02764 (25), 0.807604 (18), 0.927545 (7)	None	0.92904 (7), 0.81896 (18), 1.01966 (25)
P_{loss} (kW)	202.6863	50.7189	161.7035	42.2167	159.3392	44.484	154.9378	45.1963	158.6091	43.7611
V_{min} (pu)	0.9131	0.9734	0.9228	0.9702	0.9234	0.9695	0.9246	0.9693	0.9235	0.9697
KI_{max} (pu)	0.8250	0.4407	0.7614	0.4185	0.7552	0.4259	0.7457	0.4283	0.7544	0.4236
P_{grid} (MW)	3.9177	0.7762	3.8466	0.9796	3.7239	0.9321	3.6303	0.9131	3.7440	0.9464

Table 3

The comparison results between GO, PSO and GA for different load types of the 33-node DN

Load type	Method	OS	DG (MW) [node]	P_{loss} (kW)	V_{min} (pu)	KI_{max} (pu)	P_{grid} (MW)	Run time (s)
CON	GO	33-34-11-31-28	0.75296 (17), 0.956946 (7), 1.27957 (25)	50.7189	0.9734	0.4407	0.7762	35.9273
	PSO	33-34-10-36-28	0.622025 (14), 1.42892 (29), 0.94184 (7)	54.4019	0.9722	0.4409	0.7766	37.4004
	GA	33-34-11-30-27	0.862773 (18), 1.18178 (25), 0.851517 (7)	51.4511	0.9677	0.4466	0.8704	31.8521

Load type	Method	OS	DG (MW) [node]	P_{loss} (kW)	V_{min} (pu)	KI_{max} (pu)	P_{grid} (MW)	Run time (s)
IND	GO	33-34-11-30-28	1.01000 (25), 0.82796 (18), 0.92957 (7)	42.2167	0.9702	0.4185	0.9796	49.9023
	PSO	33-34-11-31-28	0.959144 (7), 0.71764 (17), 1.02622 (29)	43.4870	0.9745	0.4238	1.0458	51.7912
	GA	33-34-11-31-28	0.736081 (17), 1.15641 (25), 0.90156 (7)	42.3981	0.9755	0.4169	0.9539	45.8951
RES	GO	33-34-11-30-28	1.02672 (25), 0.93025 (7), 0.81882 (18)	44.4840	0.9695	0.4259	0.9321	61.9444
	PSO	33-34-10-36-28	0.598416 (14), 1.40986 (25), 0.883436 (7)	47.2139	0.9700	0.4176	0.8222	49.2917
	GA	33-34-11-31-28	0.702474 (17), 1.14352 (25), 0.931268 (7)	44.6191	0.9736	0.4257	0.9331	48.5662
COM	GO	33-34-11-30-28	1.02764 (25), 0.807604 (18), 0.927545 (7)	45.1963	0.9693	0.4283	0.9131	51.5021
	PSO	33-34-9-30-26	0.811461 (18), 0.478043 (12), 1.2393 (25)	49.1772	0.9751	0.4460	1.1507	52.0665
	GA	33-34-11-30-28	1.08529 (25), 0.848386 (7), 0.809698 (18)	45.3133	0.9694	0.4298	0.9326	44.9702
MIX	GO	33-34-11-30-28	0.92904 (7), 0.81896 (18), 1.01966 (25)	43.7611	0.9697	0.4236	0.9464	53.6650
	PSO	33-10-8-31-28	0.933365 (15), 1.15687 (25), 0.766261 (7)	45.3293	0.9663	0.4169	0.8585	56.0470
	GA	33-34-11-30-28	0.845269 (18), 0.918095 (7), 1.04324 (25)	43.8150	0.9712	0.4216	0.9089	54.8410

The boxplot plot of the smallest fitness function value obtained in each run of 20 runs of the three algorithms for different load types is presented in Figure 6. The figure shows that the fitness value obtained in each run of GO is usually lower than PSO and GA and the data concentration level of GO is also better than the two comparison algorithms. This result confirms the superiority of GO for this problem.

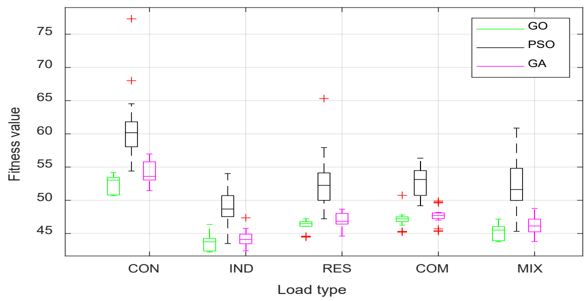


Figure 6

Boxplot of GO, PSO and GA for different load type of the 33-node DN

The comparison results with previous studies in Table 4 show that the open switches, location, and capacity of DGs obtained by the proposed GO method have smaller power loss than most previous methods. The loss reduction observed by GO is higher than 3D-GSO [5], EOA [6], IEOA [6], IEJAYA [7], FWA [19] and MPSO [18] are 3.58%, 4.81%, 2.41%, 19.72%, 8.09% and 22.32%, respectively. This comparison shows that GO is an effective method for the REC-DGA problem.

Table 4

The comparison results between GO and other methods for the 33-node DN with constant power load

Method	OS	DG (MW) [node]	P_{loss} (kW)	P_{loss} reduction (in %)
GO	33-34-11-31-28	0.75296 (17), 0.956946 (7), 1.27957 (25)	50.7189	74.98%
3D-GSO [5]	7-8-14-25-36	0.63000 (12), 0.60000 (18), 1.19000 (30)	57.9700	71.40%
EOA [6]	8-27-14-25-36	1.27900 (8), 0.63800 (14), 0.31200 (29)	60.4700	70.17%
IEOA [6]	7-9-14-27-31	0.42100 (12), 0.65000 (18), 1.15800 (29)	55.6000	72.57%
IEJAYA [7]	6-34-10-37-31	0.32003 (18), 0.36146 (10), 0.28623 (13)	90.6800	55.26%
FWA [19]	7-14-11-32-28	0.53670 (32), 0.61580 (29), 0.53150 (18)	67.1100	66.89%
MPSO [18]	2-4-6-34-35	0.58519 (17), 0.27088 (9), 0.23698 (7)	95.9500	52.66%

Conclusions

The optimal simultaneous network reconfiguration and DG allocation considering different load models has been conducted in this study. The load models consisting of CON, IND, RES, COM and MIX loads in the DN are considered for optimizing the radial configuration, location and power of DGs to minimize power loss and satisfy constraints related to the voltage and current profiles and the DG power returning to the feeders. In addition, the GO is first adapted to search the optimal open switches, location and power of DGs. The simultaneous REC-DGA problem and the GO method are implemented to find the optimal solution for the 33-node DN. The obtained results demonstrate that the power loss of the DNs has been dramatically reduced by the simultaneous REC-DGA. The power loss reduction compared to the initial configuration of the cases of constant power, industrial, residential, commercial, and mixed loads is respectively 74.98%, 73.89%, 72.08%, 70.83% and 72.41%. Furthermore, the voltage and current profiles have been enhanced after REC-DGA. Moreover, by performing the simultaneous REC-DGA, the total active load power of the industrial, residential, commercial, and mixed loads has increased by {0.55%, 2.77%, 4.47% and 2.37%} compared to the total original load. In terms of solving methods for the simultaneous REC-DGA problem, GO determines the better solutions than those of PSO and GA. The power loss gained by GO in different load types is lower than that of PSO and GA. Therefore, GO can be an efficient method for the optimal network reconfiguration and DG allocation position problem. For future works, the REC-DGA problem for different load models should be studied further considering the uncertainty of load types and DGs.

References

[1] Balu, K., Mukherjee, V.: Siting and Sizing of Distributed Generation and Shunt Capacitor Banks in Radial Distribution System Using Constriction Factor Particle Swarm Optimization. Electric Power Components and Systems, 48 (6-7), 2020, pp. 697-710

[2] Hota, A. P., Mishra, S., Mishra, D. P.: Active power loss allocation in radial distribution networks with different load models and DGs. Electric Power Systems Research, 205 (June 2021), 2022, p. 107764

[3] BP: *BP Statistical Review of World Energy 2022*. 2023, pp. 1-60

[4] Ortega-Romero, I., Serrano-Guerrero, X., Barragán-Escandón, A., Ochoa-Malhaber, C.: Optimal Integration of Distributed Generation in Long Medium-Voltage Electrical Networks. Energy Reports, 10, 2023, pp. 2865-2879

[5] Teimourzadeh, H., Mohammadi-Ivatloo, B.: A three-dimensional group search optimization approach for simultaneous planning of distributed generation units and distribution network reconfiguration. Applied Soft Computing, 88, 2020, p. 106012

[6] Shaheen, A. M., Elsayed, A. M., El-Sehiemy, R. A., Abdelaziz, A. Y.: Equilibrium optimization algorithm for network reconfiguration and distributed generation allocation in power systems. Applied Soft Computing, 98, 2021, p. 106867

[7] Raut, U., Mishra, S.: An improved Elitist – Jaya algorithm for simultaneous network reconfiguration and DG allocation in power distribution systems. Reinforced Plastics, 30 (September), 2019, pp. 92-106

[8] Uniyal, A., Sarangi, S.: Optimal network reconfiguration and DG allocation using adaptive modified whale optimization algorithm considering probabilistic load flow. Electric Power Systems Research, (April 2019), 2020, p. 106909

[9] Tolabi, H. B., Ara, A. L., Hosseini, R.: A new thief and police algorithm and its application in simultaneous recon fi guration with optimal allocation of capacitor and distributed generation units. Energy, 203, 2020, p. 117911

[10] Eid, A.: Cost-based analysis and optimization of distributed generations and shunt capacitors incorporated into distribution systems with nonlinear demand modeling. Expert Systems with Applications, 198 (May 2021), 2022, p. 116844

[11] Singh, D., Misra, R. K.: Load type impact on distribution system reconfiguration. International Journal of Electrical Power and Energy Systems, 42 (1), 2012, pp. 583-592

[12] Precup, R. E., Hedrea, E. L., Roman, R. C., Petriu, E. M., Szedlak-Stinean, A. I., Bojan-Dragos, C. A.: Experiment-Based Approach to Teach Optimization Techniques. IEEE Transactions on Education, 64 (2), 2021, pp. 88-94

[13] Milovančević, M., Milčić, D., Andjelkovic, B., Vračar, L.: Train Driving Parameters Optimization to Maximize Efficiency and Fuel Consumption. Acta Polytechnica Hungarica, 19 (3), 2022, pp. 143-154

[14] Tompa, T., Kovács, S.: Knowledge Base Optimization of the HFRIQ-Learning. Acta Polytechnica Hungarica, 21 (10), 2024, pp. 93-110

[15] Zamfirache, I. A., Precup, R. E., Petriu, E. M.: Adaptive reinforcement learning-based control using proximal policy optimization and slime mould algorithm with experimental tower crane system validation. Applied Soft Computing, 160 (April), 2024, p. 111687

[16] Precup, R., Preitl, S., Korondi, P.: Fuzzy Controllers With Maximum Sensitivity for Servosystems. IEEE Transactions on Industrial Electronics, 54 (3), 2007, pp. 1298-1310

[17] Ibrahim, S. K., Rad, M. M., Fischer, S.: Optimal Elasto-Plastic Analysis of Reinforced Concrete Structures under Residual Plastic Deformation Limitations. Acta Polytechnica Hungarica, 20 (1), 2023, pp. 45-62

[18] Kumar, D., Singh, A., Mishra, S. K., Jha, R. C., Samantaray, S. R.: A coordinated planning framework of electric power distribution system: Intelligent reconfiguration. International Transactions on Electrical Energy Systems, 28 (6), 2018, pp. 1-20

[19] Mohamed Imran, A., Kowsalya, M., Kothari, D. P.: A novel integration technique for optimal network reconfiguration and distributed generation placement in power distribution networks. International Journal of Electrical Power and Energy Systems, 63, 2014, pp. 461-472

[20] Wolpert, D. H., Macready, W. G.: No free lunch theorems for optimization. IEEE Transactions on Evolutionary Computation, 1 (1), 1997, pp. 67-82

[21] Zhang, Q., Gao, H., Zhan, Z. H., Li, J., Zhang, H.: Growth Optimizer: A powerful metaheuristic algorithm for solving continuous and discrete global optimization problems. Knowledge-Based Systems, 261, 2023, p. 110206

[22] Nguyen, T. T., Nguyen, T. T., Nguyen, H. P.: Optimal soft open point placement and open switch position selection simultaneously for power loss reduction on the electric distribution network. Expert Systems with Applications, 238 (PA), 2024, p. 121743

[23] Nguyen, T. T., Nguyen, T. T.: An improved cuckoo search algorithm for the problem of electric distribution network reconfiguration. Applied Soft Computing, 84, 2019, p. 105720

[24] Raju, E. S. N. P., Terzija, V., Guwahati, I. I. T.: *Power system loads modeling*. In: Encyclopedia of Electrical and Electronic Power Engineering. Elsevier, 2023, pp. 186-208

[25] Baran, M. E., Wu, F. F.: Network reconfiguration in distribution systems for loss reduction and load balancing. IEEE Transactions on Power Delivery, 4 (2), 1989, pp. 1401-1407

[26] Kennedy, J., Eberhart, R. C.: Particle swarm optimization. Proceedings of ICNN’95 - International Conference on Neural Networks, 1995, pp. 39-43

[27] Haupt, R. L., Haupt, S. E.: *Practical Genetic Algorithms*. John Wiley & Sons, Inc., Hoboken, New Jersey, 2004

[28] Zimmerman, R. D., Murillo-Sanchez, C. E., Thomas, R. J.: MATPOWER: Steady-State Operations, Planning, and Analysis Tools for Power Systems Research and Education. IEEE Transactions on Power Systems, 26 (1), 2011, pp. 12-19