

Distribution network reconfiguration based on artificial network reconfiguration for variable load profile

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Abstract: Network reconfiguration is a process to change the open-switches in distribution system for a minimum power loss. In the past, metaheuristic techniques were applied widely for network reconfiguration with consideration of a fixed loading profile. When the loading changes, the current configuration may not be the optimal one. Thus, the technique needs to be executed to find a new optimal configuration based on the latest loading. The process is time-consuming since metaheuristic techniques commonly require high computational times and produces inconsistent results. Therefore, this paper proposes a network reconfiguration technique based on artificial neural network (ANN) for variable loading conditions. The proposed ANN model is tested on IEEE 33-bus, IEEE 69-bus, and IEEE-118 bus systems. The test results indicate the efficiency of the proposed technique in three aspects: processing time, simple structure, and high accuracy.

Key words: Distribution system, network reconfiguration, artificial neural networks, evolutionary programming

1. Introduction

Distribution network reconfiguration (DNR) has gained very high attention due to its importance in power delivery. It was reported in the literature that the power loss in distribution system is in the range of 5% to 20% [1–3] depending on the size and configuration of the system. There are many techniques used to reduce power loss in distribution systems. DNR is primarily considered for reduction in the power loss and load balancing across the feeder. Additionally, DNR is implemented for distribution system restoration [4, 5], minimizing reverse current from distributed generations [6], and improving distribution system reliability [7]. Other techniques for power loss reduction, such as the integration of distributed generations units [8–10] and reactive power compensators [11], are used for further reduction in power loss and enhancing voltage profile [12]. Distribution network reconfiguration is the process of altering the system topology in such a way that the power loss is minimal. Due to the large number of switching elements in the system, DNR is considered a combinatorial, nondifferential, and constrained optimization problem. The process of altering the system topology is done by changing the open/close status of sectionalizing switches (normally closed) and tie switches (normally open) while maintaining the radial structure of the system without isolating any load.

A considerable amount of research has been done on loss reduction in distribution systems. The first category of approaches to solving DNR is heuristic techniques. Merlin and Back [13] proposed a heuristic branch-and-bond approach to solve DNR. Another heuristic method based on power flow was presented in

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[14]. A technique called branch exchange was proposed by [15] which was later used by [16] to obtain global or near-global solutions for DNR. Such techniques are easy to formulate; however, there is no assurance of convergence. Due to the increase of switching options and size of distribution systems, the second category of approaches, which are metaheuristic techniques, were used. Such techniques are genetic algorithm [17], particle swarm optimization [18], firefly [19], discrete evolutionary programming [20], discrete artificial bee colony [21], tabu search [22], runner root [23], and harmonic search [24]. Metaheuristic techniques have the ability to obtain global optimum solution; however, the computational time is very high. Thus, it is not suitable for practical problem.

Unlike heuristic and metaheuristic techniques, the artificial intelligence (AI) techniques can be considered, which will provide an optimum solution in a short span of time. The most popular technique is artificial neural networks (ANN). In [25], an ANN approach was proposed for power loss minimization of distribution system. The proposed method can provide a solution in both constant and load variation cases. A similar ANN approach was proposed in [26], where only one set of ANNs were used according to the number of sensitive switches for different load patterns. DNR is a complex optimization problem and when it is evaluated with variable loading, it becomes more complex. To reduce the complexity of the problem. The authors in [27] utilized ANN with a novel strategy to reduce the number of inputs to ANN by applying a dynamic fuzzy-c mean clustering technique. A similar technique based on clustering was proposed in [28].

From the above analysis, heuristics and metaheuristics categories are not suitable for variable DNR problem in two reasons: First, large computation time as such techniques determines one solution for a specific load condition, through an iterative process. Once a change occurs in the load, recalculation of DNR process is required. The second reason is inconsistency in providing optimal solution due to the random search process [20]. On the other hand, the application of ANN techniques can significantly reduce the time required for DNR process. However, there are some drawbacks of ANN technique in the application of network reconfiguration. Approaches in [25, 26] require a large number of trained neural networks to find solutions for large systems, since the number of proposed ANNs is dependent on the number of sensitive switches in the system. Additionally, reducing the amount of training data may limit the generalization capacity of neural network.

Considering the advantages of ANN, this paper proposes optimal distribution network reconfiguration to reduce power loss based on ANN technique. In this work, the proposed ANN technique is different from previous work in the following aspects: (1) The structure of ANN model is divided into smaller models. (2) Each model is associated with a tie switch in the system. (3) The optimal configuration is determined by combining the smaller ANN models. As a result, this technique has improved the accuracy of ANN prediction ability. Moreover, the proposed ANN technique facilitated the utilization of ANN for large-scale distribution systems with small number of training networks. The proposed method is tested on IEEE 33-bus, IEEE 69-bus, and IEEE 118-bus systems under static and dynamic loading conditions. The test result and comparison with other techniques in the literature revealed the proposed method's effectiveness in finding configuration in a short span of time.

The organization of this paper is as follows. Mathematical formulation and constraints are developed in Section 2. Section 3 is an overview of ANN, application of evolutionary programming (EP) to network reconfiguration is presented in Section 4. Section 5 describes the proposed ANN methodology. Tests and results are analyzed in Section 6 and conclusion is given in Section 7.

2. Mathematical formulation

The main objective for network reconfiguration is to change the power flow in distribution system by transferring heavily loaded feeders to less heavily loaded feeders. Reconfiguration should reduce the power loss and improve the voltage profile. Therefore, the main objective function of this study is:

$$\min(P_{T,loss} = \sum_{i=1}^m R_i \left(\frac{P_i^2 + Q_i^2}{V_i^2} \right)) \quad (1)$$

where m is the number of closed branches. P_i , Q_i and V_i are the active power, reactive power, and the voltage at the receiving terminal of branch i , respectively. R_i is the resistance of branch i . The objective function is subject to the following constraints. These constraints should be satisfied during the process of network reconfiguration.

The first constraint is power balance:

$$P_{sub} = \sum_{k=1}^{br} (P_{load} + P_{T,loss}) \quad (2)$$

where P_{sub} is the power supplied by the substation and P_{load} is the active power of the load. This equation implies that the power of the load and the total power loss is equal to the total power generated substation.

The second constraint is bus voltage limitation:

$$V_{min} \leq V_i \leq V_{max} \quad (3)$$

where $V_{(min)}$ and $V_{(max)}$ represent the upper and lower bound of permitted voltage (from 0.9 pu to 1.1 pu).

The third constraint is current limitation:

$$I_i \leq I_{max} \quad (4)$$

where $I_{(max)}$ is the maximum current limit of branch i .

The final constraint is the radial structure of the network. The radial structure of distribution network must be maintained during reconfiguration process and all loads must be served.

3. Overview of artificial neural network

An overview of artificial neural network (ANN) is provided in this section since it is applied for network reconfiguration. Basically, ANN consists of input layer, a number of hidden layers, and output layer. It is based on a collection of densely connected nodes called neurons, usually in a feed forward way [29]. The input layer propagates the received information to output layers through the hidden layers, where each node (neuron) has an associated weight w_{ij} . A group of data consisting of input and output can be represent by equation (5).

$$TrainingSet = [(I_1, O_1), (I_2, O_2), \dots, (I_P, O_P)] \quad (5)$$

where (I_p, O_p) represents the input and the desired output for a single training pattern.

The training process is a matter of adjusting the weights w_{ij} between neurons until a good mapping function f is achieved. The relation between input layer and hidden layer is shown in equation (6).

$$Net_{H_n} = \sum_j^h \sum_i^p x_i * w_{ij} \tag{6}$$

where $Net_{(H_n)}$ is the total output of the hidden layer n , h is the number of neurons in the hidden layer H_n , p is the number of input patterns to input layer x , and w_{ij} is the weight associated with each connection between inputs and hidden layers.

Then, equation (6) can be represented as follows:

$$Out_{H_n} = f(Net_H) \tag{7}$$

where f is the activation function of the hidden layer. Generally, the Sigmoid (logsig) activation function is selected for the nonlinear mapping. Equation (8) shows the relation between input and output of hidden layer H_n .

$$Out_{H_n} = \frac{1}{1 + e^{-(Net_H + b_H)}} \tag{8}$$

where b_H is the bias of the hidden layer.

The input to the next layer is the output of hidden layer H_n . If there is more than one hidden layer, the process is repeated as in Equations Equations (6) to (8). The training process continues until the mean square error (MSE) is minimized, which is the squared sum of the difference between the desired output and NN output for all patterns [25].

$$E(w) = \frac{1}{n} \sum_{i=1}^p (O_t - O_{NN})^2 \tag{9}$$

where O_t is the desired output; O_{NN} is NN output for single training pattern, and n is the total number of outputs.

During the learning process, the training algorithm updates the weights according to direction function $r(t)$ [27]. In this paper Levenberg-Marquardt, a second-order optimization algorithm, is applied. It is considered to be the fastest backpropagation algorithm for medium-sized NN. The algorithm can be represented by the following equations:

$$\Delta w_t = \epsilon r(t) \tag{10}$$

$$r(t) = [J^T J + \mu I]^{-1} J^T e \tag{11}$$

$$w_{t+1} = w_t + \Delta w_t \tag{12}$$

where J is the Jacobean matrix containing the first derivatives of NN errors with respect to weights and biases; e is a vector containing network errors, and ϵ is the learning rate.

4. Network reconfiguration based on evolutionary programming

In order to model the proposed ANN for network reconfiguration, a set of data of optimal configuration for different loading conditions are required. This task can be achieved by using any optimization technique. In this work, evolutionary programming (EP) is chosen due to its simplicity, reasonable convergence time and because it has been proven to work well for network reconfiguration application [20, 30]. The application of EP for network reconfiguration can be summarized in the following steps:

Step 1: Set the input data for EP such as bus data, line data, population size, maximum iteration, and minimum error.

Step 2: Generate random solutions which are the tie switches in distribution system to be opened. These switches are called population (parents), which is represented by equation 13.

$$S_{jn} = \begin{bmatrix} G_1 & G_2 & \cdots & G_n \\ S_{11} & S_{12} & \cdots & S_{1n} \\ S_{21} & S_{22} & \cdots & S_{2n} \\ \vdots & \vdots & & \vdots \\ S_{m1} & S_{m2} & \cdots & S_{mn} \end{bmatrix} \quad (13)$$

where $j = 1, 2, 3, \dots, m$ represents the population index, m represents population size, n represents the number of switches to be opened, and G is the switch group number.

Step 3: Start the EP by solving load flow analysis using Newton–Raphson for each population and get the power flow values through the entire network.

Step 4: Evaluate the fitness function for each population which means calculate the power loss for that specific configuration using equation 1.

Step 5: The initial population in step 2 undergoes mutation process in which the switch group G_1 starting from S_{11} to S_{m1} is mutated using Gaussian mutation operator as in equation 14 to produce offspring. Then the process is repeated for switch group G_2 and so on until switch group G_n .

$$S_{m+j,n} = S_{m,n} + N(0, \beta(S_{m,max} - S_{m,min})\left(\frac{f_i}{f_{max}}\right)) \quad (14)$$

where $S_{m+j,n}$ is mutated population (offspring), $S_{m,n}$ is the old population (parents), N is random Gaussian number, β is the search step, $S_{m,max}$ is the maximum random number in switch group G , $S_{m,min}$ is the minimum random number in switch group G , f_j is the fitness value for random switch population j , and f_{max} is the maximum fitness value in switch group G .

Step 6: The parents and offspring are combined in new population and sorted in an ascending order based on the fitness value. Then, the first half of the new population is selected to become the new population for the next generations.

Step 7: Finally, the process is repeated from step (4–6) until the difference between the maximum fitness value and minimum fitness value is less than minimum error (ME) as shown in equation 15. The flow chart of EP is shown in Figure 1.

$$f_{max} - f_{min} \leq ME \quad (15)$$

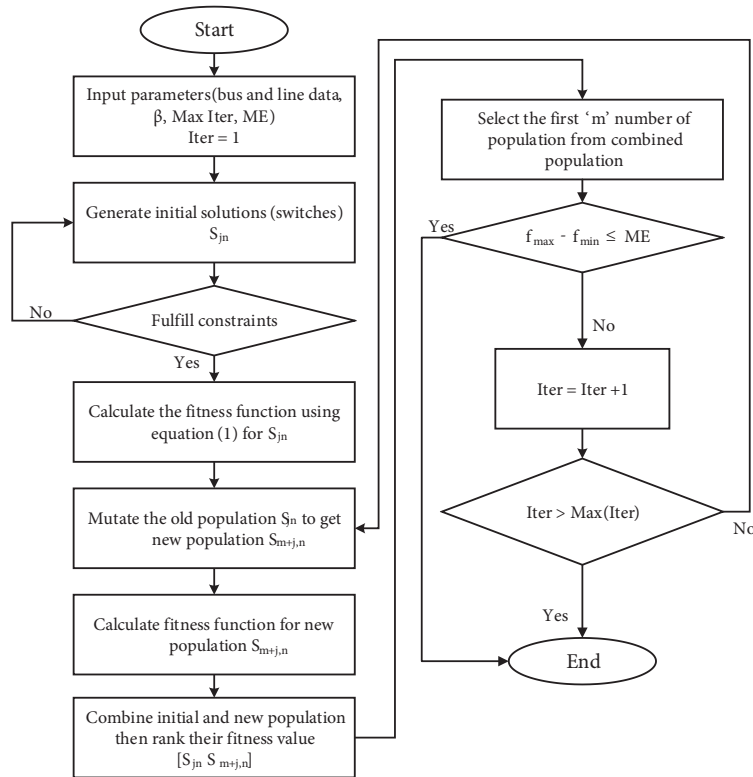


Figure 1. Network reconfiguration based on evolutionary programming.

5. Proposed methodology

5.1. Load groups

In this work, the loads in the test system are categorized into three load groups; residential, commercial, and industrial as suggested in [26]. Each load group has similar characteristics in which the changes of loads in each load group present similar behavior. The load groups can operate on estimated levels according to their peak demand load curves as shown in Figure 2. The number of estimated load levels is determined based on the range of the actual loads as shown in Table 1. As a result, the total number of load patterns will be p^m , where p and m are the load level and load group, respectively. In this case, the total number of load patterns will be 216. For each load pattern, network reconfiguration based on EP is applied to find optimal configuration having minimum power loss. These configurations and its load patterns are used as the training set for ANN.

5.2. ANN design

The proposed ANN technique for distribution system reconfiguration is shown in Figure 3. The input consists of load patterns (operating percentages of the three load groups) and the output is the switch number. The number of ANNs will be equal to the number of tie switches in the system, where each ANN will give one switch to be opened. The output of all ANNs will give optimal configuration for a specified load pattern. The relation between the input and output of DNR problem is nonlinear. Therefore, a normalization layer is added before the input layer of ANN. The purpose of this normalization layer is to normalize the switch numbers to increase the learning performance of ANN models. The normalization process is done for each group of switches associated with a particular ANN model. Thus, this process is repeated according to the number of tie switches in the system. This step changes the values of optimal switches data to be set in the range between 0 and 1.

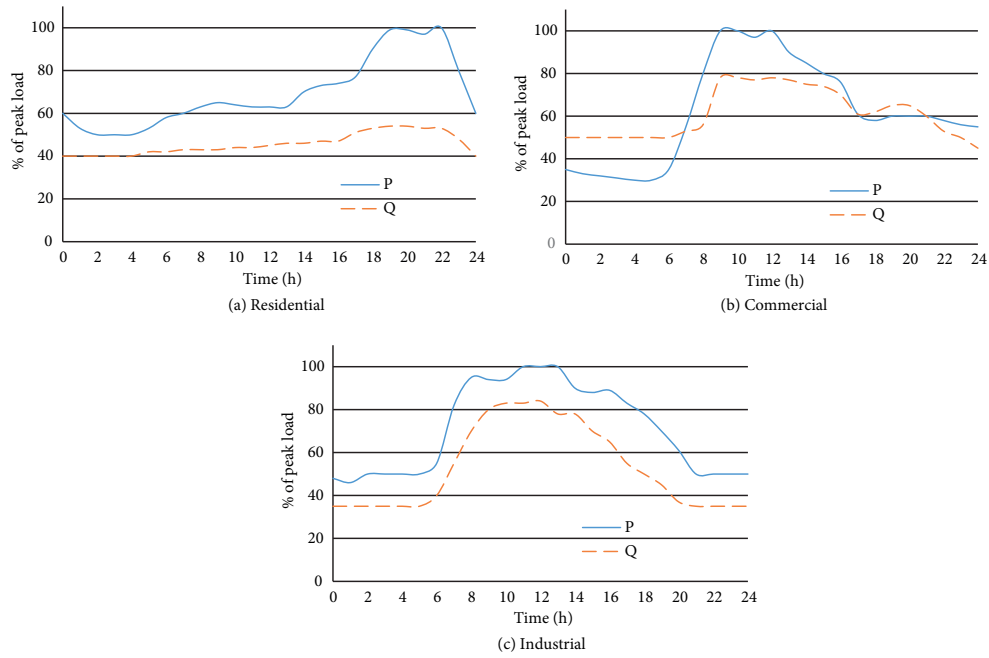


Figure 2. Daily load curves in peak load percentage.

Table 1. Estimated operating load levels.

Load level	Actual load levels (% of peak demand)	Estimated load levels (% of peak demand)
1	45 ≤ 54	50
2	55 ≤ 64	60
3	65 ≤ 74	70
4	75 ≤ 84	80
5	85 ≤ 94	90
6	95 ≤ 100	100

5.2.1. ANN training steps

Each ANN model is trained only for one switch, while the input for all ANN models does not change. The process of training is iterative, since choosing the appropriate number of neurons in the hidden layer is done by trial and error. The training will start with one neuron and then the number is increased until a good convergence is achieved. The weights are initialized as random values. During the training process, the weights are adjusted iteratively to minimize the mean-squared-error. The steps for training ANN are as follows:

Step 1: Generate the training data for ANN by using EP optimization in such a way the data is represented as follows.

$$Data = \begin{bmatrix} & G_1 & G_2 & \cdots & G_p \\ LP_1 & OS_{11} & OS_{12} & \cdots & OS_{1p} \\ LP_2 & OS_{21} & OS_{22} & \cdots & OS_{2p} \\ \vdots & \vdots & \vdots & & \vdots \\ LP_m & OS_{m1} & OS_{m2} & \cdots & OS_{mp} \end{bmatrix} \quad (16)$$

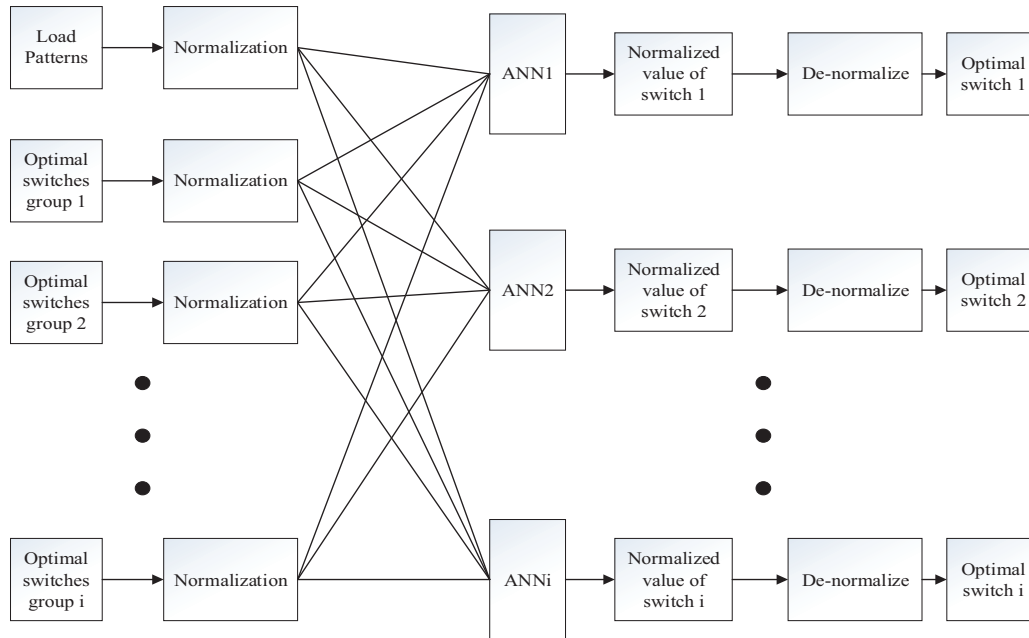


Figure 3. Proposed ANN design for distribution system reconfiguration.

where OS_{mp} is the optimal tie switch in a switch group G_p for a load pattern LP_m , m is the number of load patterns, and p is the number of switch groups. LP_m is the operating percentage for residential, commercial, and industrial loads.

Step 2: The data for training ANN is selected randomly from the generated data (70% of generated data), which consists of load patterns as inputs and optimal switches as desired output for ANN model.

Step 3: Normalize all switches in the first optimal switch group G_1 , starting from OS_{11} to OS_{m1} using equation 17, then repeat for the rest of the optimal switch groups, for $p = 2, 3, \dots, p$ (giving a matrix of $m \times p$ elements of normalized switches).

$$OS_{norm} = \frac{OS_{m1} - \min(OS_{m1})}{\max(OS_{m1}) - \min(OS_{m1})} \quad (17)$$

Step 4: Train the first ANN on the first group of optimal switches G_1 , starting with one neuron and random initial weights.

Step 5: The training process continues for specific number of iterations, while the weights are updated each iteration.

Step 6: Store the final value of weights after convergence.

Step 7: Test the network accuracy on the remaining data (30% of training data) using the weight values in step 6. RMS and absolute error are used to determine the level of learning the ANN of the data. If the RMS value is below 0.1, then the network has reached satisfactory level of training [26].

Step 8: If the accuracy is high, continue. Otherwise, the number of neurons is increased by 1, then repeat steps (4-7).

Step 9: Train the other ANN models using the same procedure from steps 4-7 based on the number of optimal group switches G_p .

5.2.2. Testing accuracy of trained ANN

The remaining 30% of generated data that was not used in the training process is new to the ANN, which means that network has not been trained on these load patterns. The ANN is evaluated based on the number of correct predictions for unseen data and the number of correct responses for seen data. This is done by using the combined ANN model to find the output of all load patterns and compare with the actual values.

6. Test and results

In this section, the proposed method was evaluated on IEEE 33-bus, IEEE 69-bus, and IEEE 118-bus systems. Two optimization techniques are used to evaluate the performance of the proposed method: EP and PSO [31]. The search step parameter in EP is set to 0.05; this value is based on a trial basis. Simulation results were performed on Intel Core 2 Duo CPU and 3 GB RAM computer using MATLAB software.

6.1. Test System 1

The IEEE 33-bus system is shown in Figure 4, the system consists of 33 buses, 32 sectionalizing switches, and 5 tie switches. The default opened tie switches are 33, 34, 35, 36, and 37 in the network. The system voltage is 12.66 kV, while the total real and reactive power loads are 3.7 MW and 2.3 MVAR, respectively. The power loss of the default operating condition is 208.459 kW and the lowest bus voltage is 0.9108 pu.

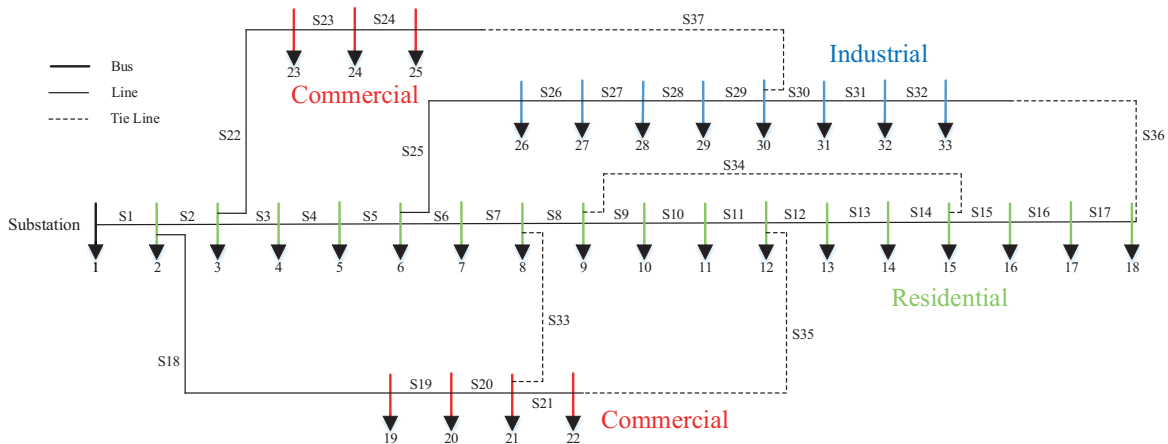


Figure 4. IEEE 33-bus distribution system.

6.1.1. Results

From the solution of network reconfiguration for 33-bus system, most of the configurations are the same, and can be grouped into six distinct configurations as tabulated in Table 2. Furthermore, it can be observed from this table that the first three tie switches do not change in all 6 configurations. Therefore, two ANNs are used for the training which are ANN4 and ANN5. The final structure of the training network is determined based on the most accurate results of ANN models. While the structures of both ANNs are similar regarding input and output neurons, the numbers of neurons in the hidden layer are different.

Table 3 shows the performance of each ANN model based on the mean square error and the absolute error. ANN4 accuracy is 99.07% which corresponds to 214 optimal solutions for switch group 4 out of 216 load

patterns while ANN5 gives 100% optimal solution for switch group 5. The overall accuracy of the final solution (combination ANN4 and ANN5 models) is 99.07%. It was identified that for ANN4, inaccuracy occurred for load pattern 42 and load pattern 195. For these load patterns, the final solution of switches for the proposed ANN and EP optimization are presented in Table 4. Although the solution of ANN is different from the optimization solution based on EP, only one switch is different from the optimization solution and the power loss differences between two techniques are also small.

In order to verify the proposed ANN technique, a comparison with other published studies is provided in Table 5. The optimal configurations obtained from references that used fireworks algorithm (FWA) [19], discrete evolutionary (DEP) [20], harmony search algorithm (HAS) [24], cuckoo search algorithm (CSA) [32] were reevaluated at 100% loading to determine the power loss using the same load flow program (from MATPOWER) as in this work. The results are presented in Table 5. It can be observed that there is a slight difference between the references and recalculated one. This might be due to difference in load flow program/method and computer processor used in the referred papers. The proposed ANN method obtained the optimal solutions as in other references except [19], which is higher than others. The optimal configuration is 7, 9, 14, 32, 37, which results in 33.35% power loss reduction. Figure 5 shows the 33-bus test system after reconfiguration using ANN.

Table 6 shows the results obtained from EP and PSO. Both algorithms give optimal configuration and power loss value. However, the time needed to find the optimal configuration to minimize the power loss is 30.47s for EP, 18.65s for PSO, respectively. On the other hand, the time for the proposed method is 0.052 s, which is shorter compared to both techniques. Moreover, for 200 iterations, the consistency of the proposed method to give optimal configuration is 100%, while for other techniques it is 25% for EP and 32% for PSO.

Figure 6 shows the voltage profile of the distribution network before and after the reconfiguration for 100% loading condition. The minimum voltage of the system has improved by 3.35%, while the minimum bus voltage in all load patterns before and after reconfiguration has improved by an average of 2.37%.

Table 2. Optimal configurations of IEEE 33-bus distribution system.

Optimal configuration number	Tie switches to be opened	Load patterns numbers
1	S7, S9, S14, S32, S37	1, 7, 8, 13, 14, 19, 20, 25, 26, 31, 32, 43, 44, 49, 50, 51,55, 56, 57, 61, 62, 63, 67, 68, 69, 79, 85, 86, 87, 91, 92,93, 94, 97,98, 99, 100, 103, 104, 105, 106, 122, 128, 129, 130, 134, 135, 136
2	S7, S9, S14, S32, S28	2, 3, 4, 37, 38, 39, 40, 41, 42, 45, 46, 47, 74, 75, 76, 77, 78, 80, 81, 82, 83, 84, 88, 89, 90, 96, 111, 112, 113, 114, 116, 117, 118, 119, 120, 123, 124, 125, 126, 131, 132, 148, 149, 150, 153, 154, 155, 156
3	S7, S9, S14, S31, S28	5, 6, 10, 11, 12, 18, 48, 53, 54
4	S7, S9, S14, S31, S37	9, 15, 16, 17, 21, 22, 23, 24, 27, 28, 29, 30, 33, 34, 35, 36, 52, 58, 59, 60, 64, 65, 66, 70, 71, 72, 95, 101, 102, 107, 108
5	S7, S9, S14, S36, S28	73, 109, 110, 145, 146, 147, 151, 152, 181, 182, 183, 184, 187, 188, 189, 193, 194, 195
6	S7, S9, S14, S36, S37	115, 121, 127, 133, 139, 157, 163, 169, 175, 199, 200, 205, 206, 211, 212

Table 3. ANN models' performances for IEEE 33-bus system.

ANN Number	Structure	Accuracy	MSE	Training results			Testing results		
				Cases	Correct	Alter	Cases	Correct	Alter
ANN4	3-3-1	99.07%	2.2e-04	151	151	-	65	63	2
ANN5	3-2-1	100%	1.7e-08	151	151	-	65	65	-
Combined ANN	-	99.07%	-	151	151	-	65	63	2

Table 4. Comparison between optimal configuration and ANN alternative response for IEEE 33-bus system.

Load pattern	Optimal switches	Power loss (kW)	ANN switches	Power loss (kW)
42	7, 9, 14, 32, 28	75.737	7, 9, 14, 31, 28	76.289
195	7, 9, 14, 36, 28	86.971	7, 9, 14, 32, 28	87.083

Table 5. Comparative analysis of reconfiguration methods for the IEEE 69-bus system.

	Tie switches opened	Power loss (kW)		Loss reduction (%) (based on recalculation)	V_{min} (pu)
		Reference	Recalculated		
Initial configuration	33, 34, 35, 36, 37	-	208.459	-	0.9108
HSA[24]	7, 9, 14, 32, 37	138.06	138.928	33.35	0.9423
DEP[20]	7, 9, 14, 32, 37	138.928	138.928	33.35	0.9423
CSA[32]	7, 9, 14, 32, 37	138.87	138.928	33.35	0.9423
FWA[19]	7, 9, 14, 28, 32	139.98	139.982	32.85	0.9413
Proposed ANN method	7, 9, 14, 32, 37	-	138.928	33.35	0.9423

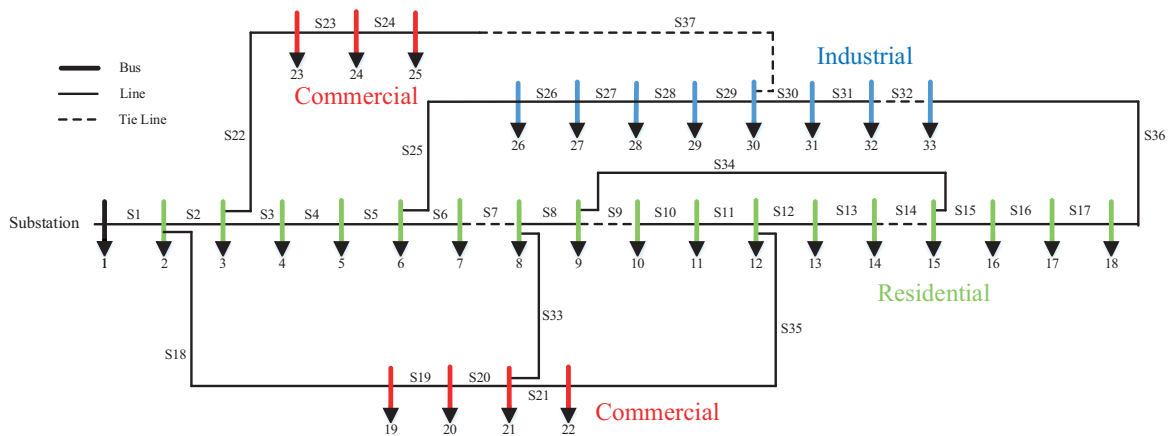


Figure 5. Comparison of simulation results for IEEE 33-bus system

Table 6. Comparative analysis of DNR between optimization techniques and proposed method for 33-bus system.

	Tie switches opened	Power loss (kW)	Loss reduction (%)	V_{min} (pu)	Consistency (%)
EP	7, 9, 14, 32, 37	138.928	33.35	0.9423	25
PSO	7, 9, 14, 32, 37	138.928	33.35	0.9423	32
Proposed ANN method	7, 9, 14, 32, 37	138.928	33.35	0.9423	100

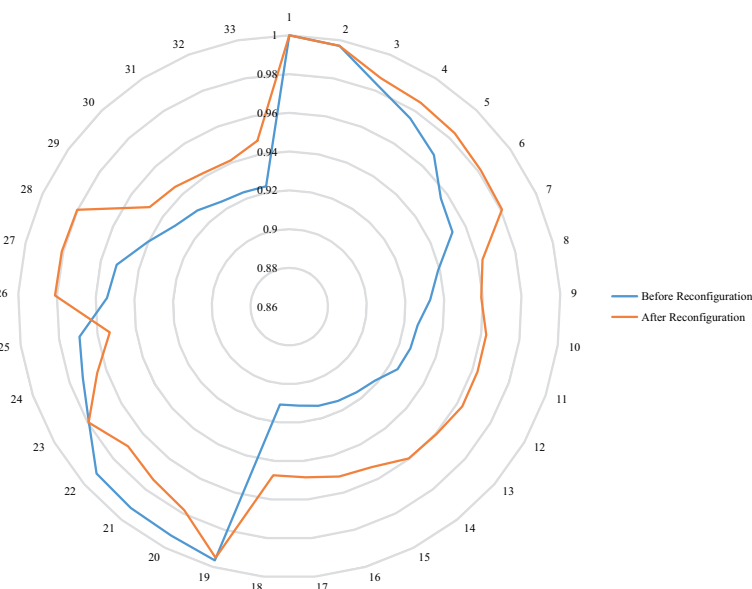


Figure 6. Voltage profile before and after reconfiguration based on ANN for IEEE 33-bus system.

6.2. Test system 2

The IEEE 69-bus system is shown in Figure 7, the system consists of 69 buses, 68 sectionalizing switches, and 5 tie switches. The default opened tie switches are 17, 22, 25, 58, and 37 in the original network. The system voltage is 12.66 kV, while the total real and reactive power loads are 3.8 MW and 2.7 MVAR respectively. The power loss of the default operating condition is 224.975 kW and the lowest bus voltage is 0.90929 pu.

6.2.1. Results

From the solution of network reconfiguration for 69-bus system, most of the configurations are the same, and can be grouped into four distinct configurations as tabulated in Table 7. Switch group 4 is the only changing group with switch numbers 62, 63, 64, and 65; thus, only 1 ANN is needed for training in this case. The structure of the training network is determined based on the most accurate results of ANN models. While the structure of the ANN model is similar to previous system in the input and output layers, the number of neurons in the hidden layer is different.

Table 8 shows the performance of the ANN model, to evaluate the performance of ANN model, the mean square error and the absolute error is used, which represents the accuracy of each ANN model. ANN4 accuracy is 100% which corresponds to 216 optimal solutions for switch group 4 out of 216 load patterns.

In order to verify the proposed ANN technique, a comparison with other published works from the literature is conducted. Four references are considered; fireworks algorithm (FWA) [19], discrete artificial bee

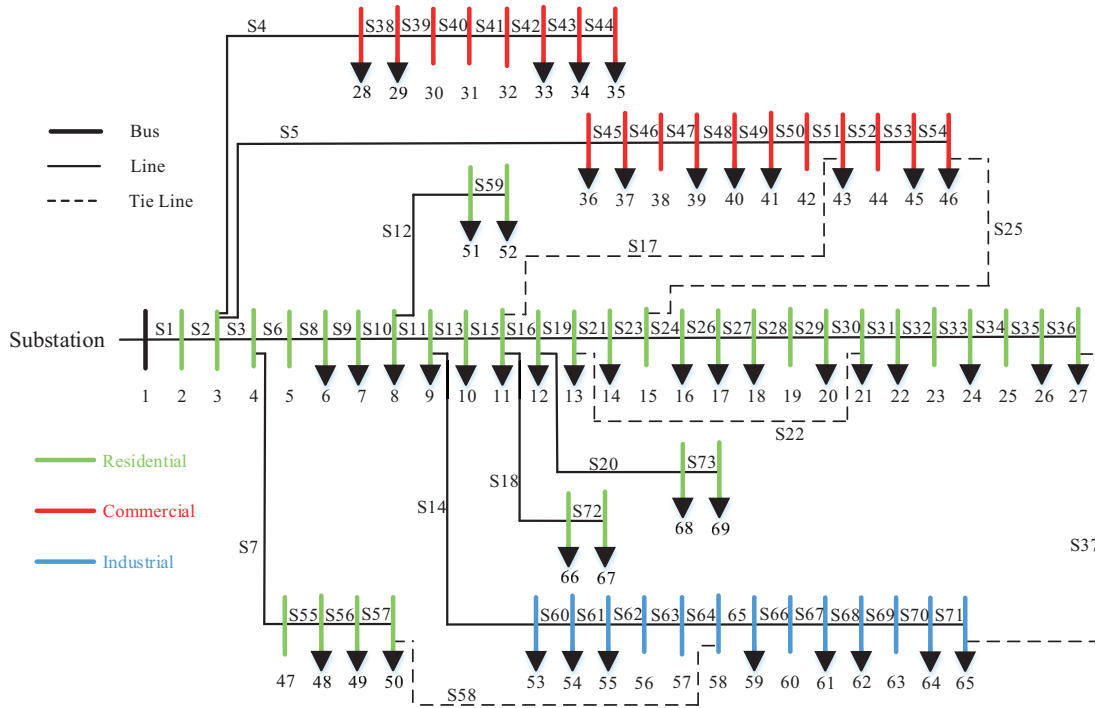


Figure 7. IEEE 69-bus distribution system.

colony (DABC) [21], adaptive cuckoo search algorithm (ACSA) [33], and fast nondominated sorting genetic algorithm (FNSGA) [34]. Similar to what is done in test of 33-bus system, the optimal configurations obtained from the referred references are reevaluated at 100% loading to determine the power loss using the same load flow program as in this work. The results are presented in Table 9. It can be observed that there is a slight difference between the references and the recalculated one. The proposed ANN method obtained optimal solutions as other comparison methods, which results in 56.37% power loss reduction. The optimal configurations are similar except for switches 55, 56, and 57. However, the obtained power loss is similar as shown in the table. The 69-bus test system after reconfiguration is shown in Figure 8.

Table 10 shows the results obtained from EP and PSO. Both algorithms give optimal configuration and power loss value. However, the time needed to find the optimal configuration to minimize the power loss is 26.475 s for EP and 21.338 s for PSO. On the other hand, the time for the proposed method is 0.054 s, which is shorter compared to both techniques. Moreover, for 200 iterations, the consistency of the proposed method to give optimal configuration is 100%, while for other techniques it is 40% for EP and 50% for PSO.

Figure 9 shows the voltage profile of the distribution network before and after the reconfiguration for 100% loading condition. The minimum voltage of the system has improved by 2.27%, while the minimum bus voltage in all load patterns before and after reconfiguration has improved by an average of 1.79%.

6.3. Test system 3

The IEEE 118-bus system is shown in Figure 10, the system consists of 118 buses, 118 sectionalizing switches, and 15 tie switches. The default opened tie switches are from 119 to 133 in the original network. The system voltage is 11 kV, while the total real and reactive power loads are 22.709 MW and 17.041 MVAR, respectively. The power loss of the default operating condition is 1298.09 kW and the lowest bus voltage is 0.8688 pu.

Table 7. Optimal configurations of IEEE 69-bus distribution system.

Optimal configuration number	Tie switches to be opened	Load patterns numbers
1	S17, S22, S23, 62, S68	1,8,17,19,20,32,37,38,40,48,51,58,59,62,63,64,76,83,91,100,101,104, 112, 117,121,122,124,125,127,128,129,133,138,140,151,152,153,154, 164,165,167,168,173,177,181,182,187,198,199,204,205,206,209
2	S17, S22, S23, 63, S68	2,11,15,21,26,27,28,31,33,36,39,46,47,54,61,69,70,71,75,78,80,90,92, 93,105,106,109,111,113,116,130,135,136,139,143,145,147,149, 158,161,169,175,178,189,191,192,193,195,196,200,202,210,215
3	S17, S22, S23, 64, S68	3,6,12,14,23,29,30,34,42,45,49,50,52,55,60,77,86,87,94,96,98,102,108, 118,123,131,141,142,144,148,155,159,160,162,163,166,170, 172,176,180,185,186,190,194,201,203,208,216
4	S17, S22, S23, 65, S68	4,5,7,9,10,13,16,18,22,24,25,35,41,43,44,53,56,57,65,66,67,68,72,73, 74,79,81,82,84,85,88,89,95,97,99,103,107,110,114,115,119,120,126, 132,134,137,146,150,156,157,171,174,179,183,184,188,197

Table 8. ANN models performance for IEEE 33-bus system.

ANN number	Structure	Accuracy	MSE	Training results			Testing results		
				Cases	Correct	Alter	Cases	Correct	Alter
ANN4	3-4-1	100%	1.2e-04	151	151	-	65	65	0

Table 9. Comparative analysis of reconfiguration methods for the IEEE 69-bus system.

	Tie switches opened	Power loss (kW)		Loss reduction (%) (based on recalculation)	V_{min} (pu)
		Reference	Recalculated		
Initial configuration	69, 70, 71, 72, 73	-	224.975	-	0.90929
ACSA[33]	14, 57, 61, 69, 70	98.59	98.161	56.37	0.9982
FWA[19]	14, 56, 61, 69, 70	98.59	98.161	56.37	0.9982
FNSGA[34]	14, 55, 61, 69, 70	98.59	98.161	56.37	0.9982
DABC[21]	14, 55, 61, 69, 70	98.59	98.161	56.37	0.9982
Proposed ANN method	14, 55, 61, 69, 70	-	98.161	56.37	0.9982

Table 10. Comparison of simulation results for IEEE 69-bus system.

	Tie switches opened	Power loss (kW)	Loss reduction (%)	V_{min} (pu)	Consistency (%)
EP	14, 55, 61, 69, 70	98.161	56.37	0.9528	40
PSO	14, 55, 61, 69, 70	98.161	56.37	0.9528	50
Proposed ANN method	14, 55, 61, 69, 70	98.161	56.37	0.9528	100

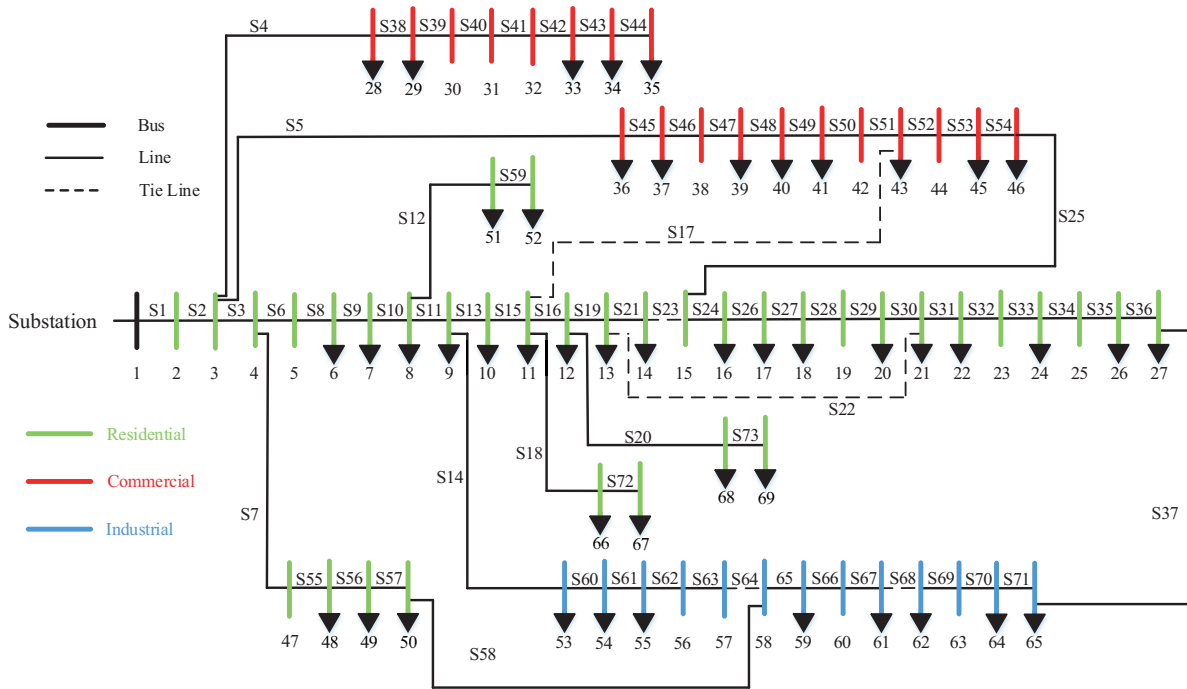


Figure 8. IEEE 69-bus distribution system after reconfiguration.

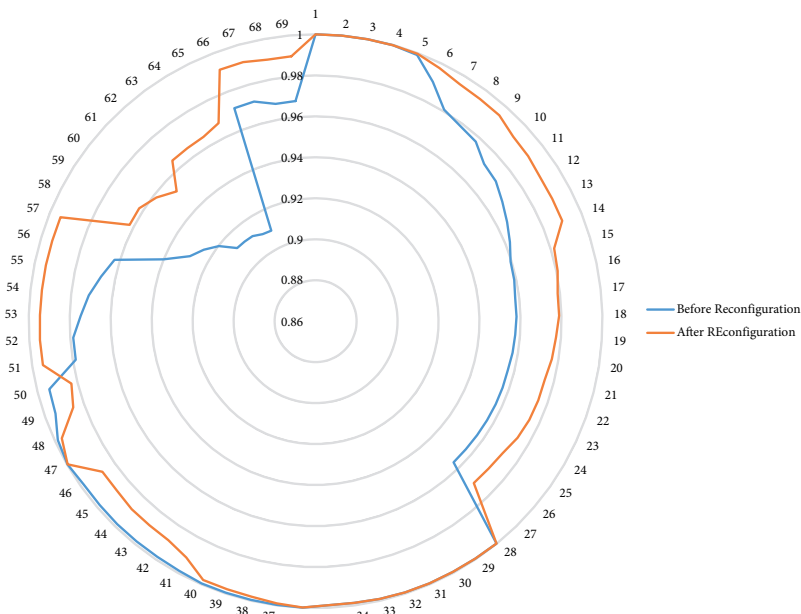


Figure 9. Voltage profile before and after reconfiguration based on ANN for IEEE 69-bus system.

6.3.1. Results

From the solution of network reconfiguration for 118-bus system, most of the configurations are the same, and can be grouped into seven distinct configurations as tabulated in Table 11. Switch groups 6, 7, 8, 9, and 11 are the changing group; thus, 5 ANNs are needed for training in this case. The structure of the training network

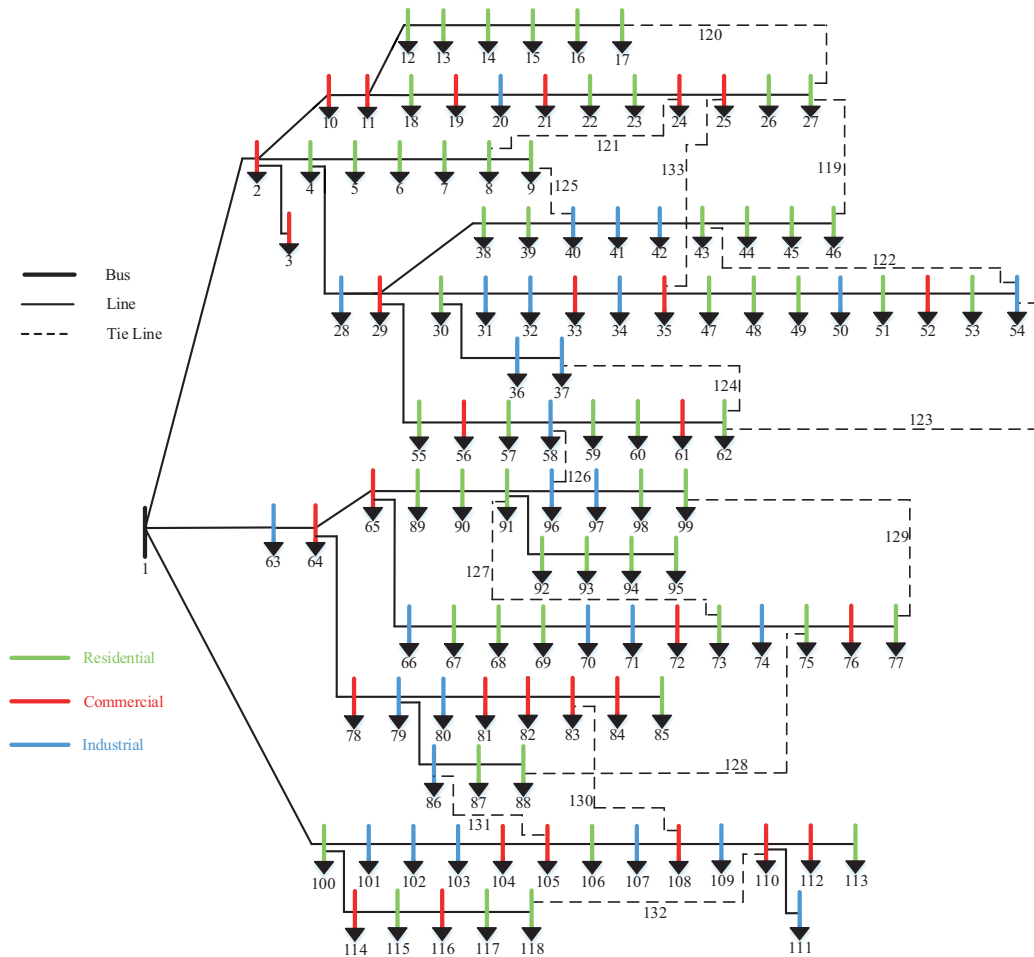


Figure 10. IEEE 118-bus distribution system.

is determined based on the most accurate results of ANN models. While the structure of the ANN model is similar to previous system in the input and output layers, the number of neurons in the hidden layer is different.

Table 12 shows the performance of each ANN model based on the mean square error and the absolute error. ANN6, ANN7, ANN8, and ANN11 have accuracy of 99.54% which corresponds to 215 optimal solutions out of 216 load patterns while ANN9 gives 100% optimal solution for switch group 9. The overall accuracy of the final solution (combination ANN4 and ANN5 models) is 99.15%. It was identified that for ANN6, ANN7, ANN8, and ANN11, inaccuracy occurred for load pattern 7, load pattern 60, and load pattern 145. For these load patterns, the final solution of switches for the proposed ANN and EP optimization are presented in Table 13. Although the solution of ANN is different from the optimization solution based on EP, the power loss differences between two techniques are small.

In order to verify the proposed ANN technique, a comparison with other published works from the literature is conducted. Three references are considered; fireworks algorithm (FWA) [35], improved tabu search (ITS) [36], and two-stage firefly algorithm [37]. Similar to what is done in test of 33-bus system, the optimal configurations obtained from the referred references are reevaluated at 100% loading to determine the power loss using the same load flow program as in this work. The results are presented in Table 14. It can be

Table 11. Optimal configurations of IEEE 118-bus distribution system.

Optimal configuration number	Tie switches to be opened	Load patterns numbers
1	S24, S26, S35, S40, S43, S51, S59, S72, S75, S96, S98, S110, S122, S130, S131	1,2,3,4,8,12,15,16,17,18,23,24,28,29,36,39,45,47,49,50,51,53, 61,64,66,68,73,74,75,85,88,89,95,96,100,104,107,112, 116,118,123,132,134,136,139,156,162,165,166,168, 174,175,176,178,181,189,191,193,197,201,203,206,216
2	S24, S26, S35, S40, S43, S51, S59, S73, S75, S96, S98, S110, S122, S130, S131	13,31,35,57,58,59,69,71,81,86,102,105,110,111, 117,126,127,130,137,148,155,167,171,173,188, 196,198,208,213
3	S24, S26, S35, S40, S43, S51, S59, S71, S75, S96, S77, S110, S122, S130, S131	9,33,46,78,98,103,109,113,121,144,150,152,160, 164,177,185,187,195,207,214
4	S24, S26, S35, S40, S43, S52, S59, S72, S75, S96, S98, S110, S122, S130, S131	5,26,34,56,62,63,65,72,83,91,97,125,133,138,140, 141,151,153,159,170,179,180,182,190,204
5	S24, S26, S35, S40, S43, S53, S59, S72, S75, S96, S98, S110, S122, S130, S131	19,20,21,22,30,32,67,76,77,79,80,82,84,87,90,92, 93,99,106,114,115,122,128,129,131,135,142,146, 157,161,163,169, 205
6	S24, S26, S35, S40, S43, S51, S62, S72, S75, S96, S98, S110, S122, S130, S131	6,7,14,37,40,43,44,48,52,54,55,70,94,101,108,119, 120,124,143,147,158,183,194,199,209,212,215
7	S24, S26, S35, S40, S43, S51, S61, S72, S75, S96, S77, S110, S122, S130, S131	10,11,25,27,38,41,42,60,145,149,154, 172,184, 186,192, 200,202,210,211

observed that there is a slight difference between the references and recalculated one. The proposed ANN method obtained optimal solutions as other methods compared except [36], which is higher than others. The optimal configuration results in 34.21% power loss reduction. The 118-bus test system after reconfiguration is shown in Figure 11.

Table 15 shows the results obtained from EP and PSO. Both algorithms give optimal configuration and power loss value. However, the average time needed to find the optimal configuration to minimize the power loss is 568.47 s for EP and 434.69 s for PSO. On the other hand, the time for the proposed method is 0.064 s, which is much shorter compared to both techniques. Moreover, for 200 iterations, the consistency of the proposed method to give optimal configuration is 100%, while for other techniques is 12% for EP and 36% for PSO.

Table 12. ANN models performance for IEEE 118-bus system.

ANN Number	Structure	Accuracy	MSE	Training Results			Testing results		
				Cases	Correct	Alter	Cases	Correct	Alter
ANN6	3-3-1	99.54%	7.3e-04	151	151	-	65	64	1
ANN7	3-3-1	99.54%	1.2e-08	151	151	-	65	64	1
ANN8	3-3-1	99.54%	4.3e-04	151	150	1	65	65	-
ANN9	3-2-1	100%	5.8e-04	151	151	-	65	65	-
ANN11	3-2-1	99.54%	3.1e-04	151	151	-	65	64	1
Combined ANN	-	98.15%	-	151	150	1	65	62	3

Table 13. Comparison between optimal configuration and ANN alternative response for IEEE 118-bus system

Load pattern	Optimal switches	Power loss (kW)	ANN switches	Power loss (kW)
7	24, 26, 35, 40, 43, 51, 62, 72, 74, 96, 98, 110, 112, 130, 131	315.385	24, 26, 35, 40, 43, 53, 62, 71, 74, 96, 98, 110, 112, 130, 131	316.231
60	24, 26, 35, 40, 43, 51, 59, 71, 74, 96, 77, 110, 112, 130, 131	343.283	24, 26, 35, 40, 43, 51, 59, 71, 74, 96, 98, 110, 112, 130, 131	344.194
145	24, 26, 35, 40, 43, 51, 59, 71, 74, 96, 77, 110, 112, 130, 131	343.733	24, 26, 35, 40, 43, 51, 61, 71, 74, 96, 77, 110, 112, 130, 131	345.421

Table 14. Comparative analysis of reconfiguration methods for the IEEE 118-bus system.

	Tie switches opened	Power loss (kW)		Loss reduction (%) (based on recalculation)	V_{min} (pu)
		Reference	Recalculated		
Initial configuration	119 to 133	-	1298.092	-	0.90929
FWA[35]	24, 26, 35, 40, 43, 51, 59, 72, 75, 96, 98, 110, 122, 130, 131	854.06	854.031	34.21	0.9982
ITS[36]	43, 27, 24, 52, 120, 59, 40, 96, 75, 72, 98, 130, 131 110, 35	865.865	871.656	32.85	0.9321
Two-stage FA[37]	24, 26, 35, 40, 43, 51, 59, 72, 75, 96, 98, 110, 122, 130, 131	853.58	854.031	34.21	0.9982
Proposed ANN method	24, 26, 35, 40, 43, 51, 59, 72, 75, 96, 98, 110, 122, 130, 131	-	854.031	34.21	0.9323

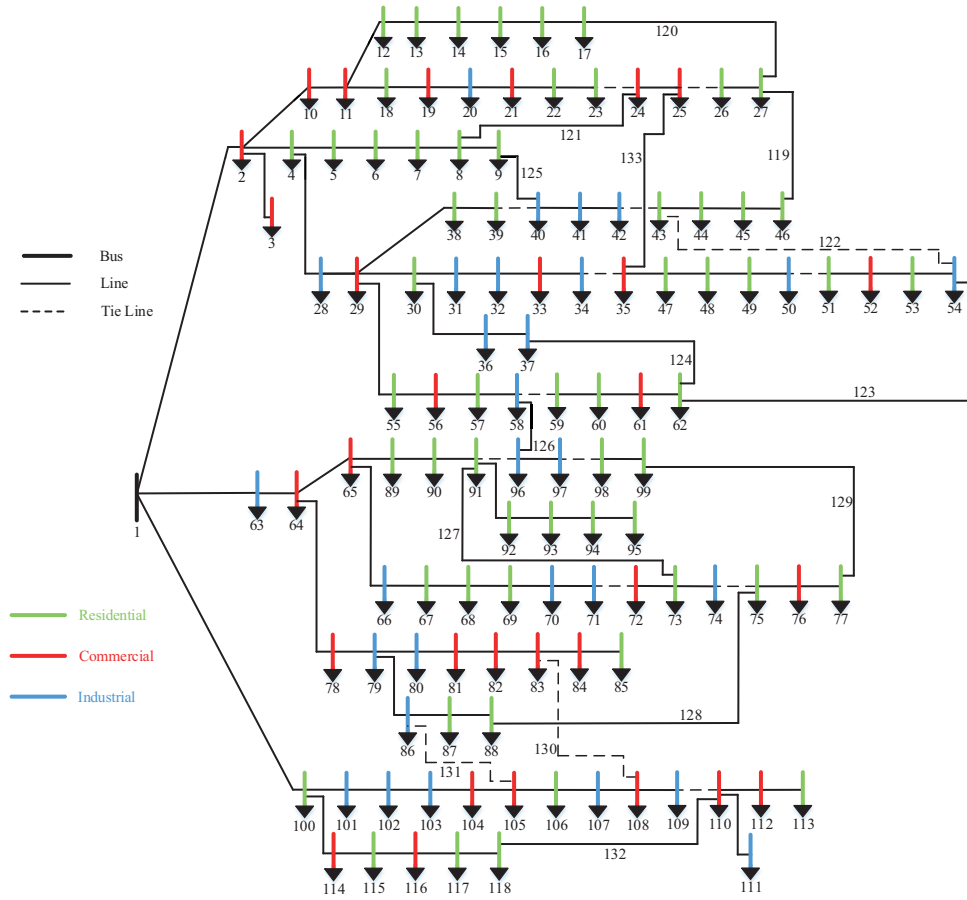


Figure 11. IEEE 118-bus distribution system after reconfiguration.

Table 15. Comparison of simulation results for IEEE 118-bus system.

	Tie switches opened	Power loss (kW)	Loss reduction (%)	V_{min} (pu)	Consistency (%)
EP	24, 26, 35, 40, 43, 51, 59, 72, 75, 96, 98, 110, 122, 130, 131	854.031	34.21	0.9323	12
PSO	24, 26, 35, 40, 43, 51, 59, 72, 75, 96, 98, 110, 122, 130, 131	854.031	34.21	0.9323	36
Proposed ANN method	24, 26, 35, 40, 43, 51, 59, 72, 75, 96, 98, 110, 122, 130, 131	854.031	34.21	0.9323	100

Figure 12 shows the voltage profile of the distribution network before and after the reconfiguration for 100% loading condition. The minimum voltage of the system has improved by 2.53%, while the minimum bus voltage in all load patterns before and after reconfiguration has improved by an average of 1.67%.

Finally, the proposed method is compared with other ANN techniques from the literature as shown in Table 16. The accuracy of the proposed method is 99.07% and 100% for 33-bus and 69-bus test system,

respectively, which are higher than other methods. Additionally, the number of load patterns introduced to the proposed ANN model is larger than other methods, which improves the generalization and learning ability of the proposed ANN method. However, the number of required neurons in the training process is small and similar to other methods, which implies the effectiveness of the proposed ANN method.

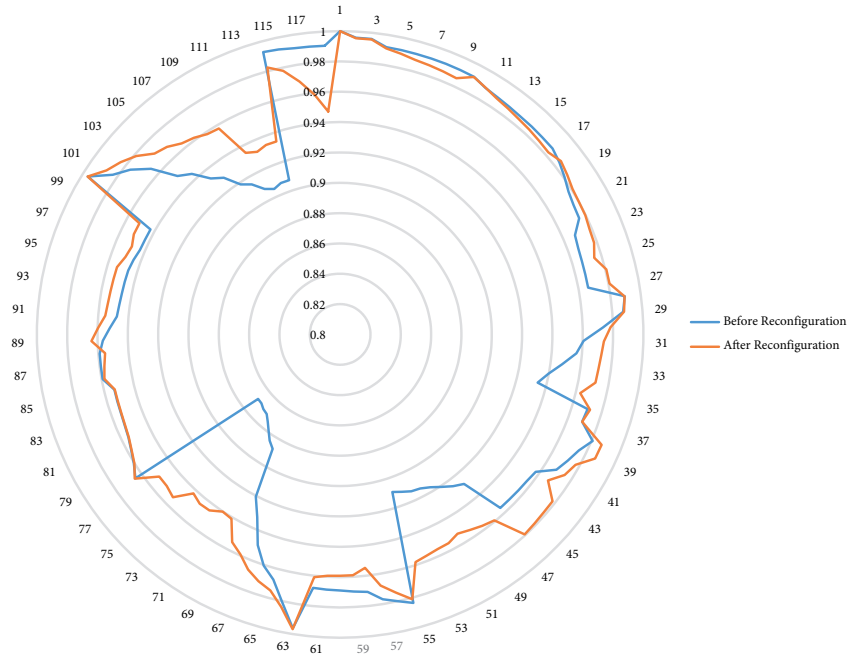


Figure 12. Voltage profile before and after reconfiguration based on ANN for IEEE 118-bus system.

Table 16. Comparison between proposed ANN model and published ANN work for network reconfiguration.

	Test system	Structure	Pretraining operation	Number of load patterns	Accuracy (%)	Processing time (s)	Processor (GHz)
ANN[27]	16-bus system	12-20-7	Clustering	64	96.67	0.993	2.0
ANN[28]	33-bus system	14-3-8	Clustering	64	98	0.37	2.2
	69-bus system	16-3-9		64	98	0.51	
Proposed ANN	33-bus system	3-3-1	None	216	99.07	0.052	2.0
	69-bus system	3-4-1		216	100	0.054	
	118-bus system	3-3-1		216	98.15	0.064	

7. Conclusion

In this work, an ANN has been proposed for successfully solving the distribution network reconfiguration problem by obtaining the optimal configuration, in which the power loss is minimal. The proposed method was tested

on IEEE 33-bus and IEEE 69-bus test systems. The optimal configuration obtained by the proposed method for 100% loading condition is similar to other techniques with an improvement in the power loss reduction by 33.35% and 56.37% for 33-bus and 69-bus test systems, respectively. Furthermore, the proposed method outperforms other methodologies in processing time, where the average time taken by proposed ANN technique is 0.052 s for 33-bus system, while it is 0.054 s for 69-bus system. Moreover, the proposed technique achieved higher accuracy than other compared ANN techniques. The comparative results verified the efficiency and high accuracy of the proposed ANN technique.

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