

A hybrid approach of artificial neural network-particle swarm optimization algorithm for optimal load shedding strategy

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ABSTRACT

This paper proposes an under-frequency load shedding (UFLS) method by using the optimization technique of artificial neural network (ANN) combined with particle swarm optimization (PSO) algorithm to determine the minimum load shedding capacity. The suggested technique using a hybrid algorithm ANN-PSO focuses on 2 main goals: determine whether process shedding plan or not and the distribution of the minimum of shedding power on each demand load bus in order to restore system's frequency back to acceptable values. In the hybrid algorithm ANN-PSO, the PSO algorithm takes responsible for searching the optimal weights in the neural network structure, which can help to optimize the network training in terms of training speed and accuracy. The distribution of shedding power at each node considering the primary control and secondary control of the generators' unit and the phase electrical distance between the outage generators and load nodes. The effectiveness of the proposed method is experimented with multiple generators outage cases at various load levels in the IEEE-37 Bus scheme where load shedding cases are considered compared with other traditional technique.

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1. INTRODUCTION

Load shedding in an electrical system is a very complex and fast process. Operational failures are unpredictable and the time required to implement load shedding is also very short. Therefore, traditional load shedding methods using under-frequency load shedding relays (UFLS), or under voltage load shedding relays (UVLS) [1]–[5] are not fast enough for emergencies. The actual load shedding system takes place in real time, and in this part, the fast response of the neural network can provide the optimal and responsive load recognition and shedding under instantaneous conditions. This method of adaptive load shedding using neural networks has been developed in [6], [7]. Furthermore, the literature [5] indicated that the response speed of the artificial neural network (ANN) algorithm is faster than other methods. However, ANN also has limitations such as system type, system dimension, impact function, learning factors, and amount of training sets [8].

At present, intelligent computing techniques have been widely implemented in the power system. This is due to the robustness and flexibility of these algorithms in solving nonlinear problems. Meta-heuristic algorithms such as: ANN [9]–[12], genetic algorithm (GA) [13], and particle swarm optimization (PSO) [14], have been proposed to determine the lowest amount of shedding power that maximizes the benefit of the system.

In particular, the ANN is an information processing template that is modelled based on the activity of the people nervous system. In an ANN, the weight represents the importance (strength) of the input data to the information processing. Learning processing of ANN is actually the process of adjusting the weights of the input data to get the desired result. Back-propagation (BP) is the most commonly used learning method. To solve problems in power systems, ANN often use network types such as general regression neural network (GRNN), back propagation neural network (BPNN). In particular, back propagation neural network (BPNN) is an algorithm that is effectively used to improve training of artificial neural networks (ANNs). Its performance at a large scale depends on the structure of the different learning model and algorithms used to compute and reduce its error in the learning process. However, BPNN has two major drawbacks: low convergence speed and instability. Today, some recent researches had been studied to limit the disadvantages of BPNN networks by improving the network structure. In [15], the author had proposed to improve the connection weights of the neural network by combining the ant colony optimization algorithm (ACO) with ANN. The results of this method can be given in a high performance but the algorithm also has limitations such as long training time, and the performance of the algorithm is highly dependent on the settings. Unlike ACO, PSO algorithm is a search algorithm based on swarm regression, it does not require any data structure information and highly effective in global search problems [16].

The objective of this paper is to show the efficiency of hybridizing PSO algorithm with ANN network. With the support of the PSO algorithm, the proposed method can determine the link weights in the ANN faster to shorten the computational process of setting the appropriate weights in the network. That saves the time to train the network but still generates the neural network with high accuracy. Load shedding control strategies consider to the primary and secondary control of generators to minimize the capacity of load reduction. The distribution of the capacity of load reduction at each load node of the system is made based on the phase electrical distance between the loads and the outage generator.

2. METHOD

2.1. Optimal quantity of load reduction capacity

The frequency response of the power system when a generator failure occurs, includes the following processes: primary frequency control and secondary frequency control. In this paper, the frequency response of the power grid takes into account the influence of frequency dependent loads [16]. After this process end, if the frequency is even not within the allowable parameter, then load reduction have to perform. Details of these processes have been presented in [17]. Computing the minimum shedding power helps to minimize damage to customers while restoring the frequency to the allowable value. In [17], the optimum amount of load reduction capacity is expressed as (1):

$$\Delta P_{LSmin} = \Delta P_L + \frac{\Delta f_{allow}}{f_0} \cdot \beta - \Delta P_{Secondary\ control\ max} \quad (1)$$

In which,

$$\Delta P_L = \frac{-\Delta f_1}{f_n} \cdot \beta \text{ is status of power balance}$$

$$\beta = P_L \cdot D + \sum_{i=1}^{n-1} \frac{P_{G_{n,i}}}{R_i} \text{ (} P_{G_{n,i}} \text{ is the rated power of the } i^{th} \text{ generator)}$$

$$R = \frac{\Delta f}{\Delta P_G} \text{ is the drop of the adjustment characteristic}$$

$$\Delta P_G = \frac{-P_{Gn}}{R} \cdot \frac{\Delta f}{f_n} \text{ is the relationship between power variation and frequency variation}$$

D is the percentage characteristic of the change of load according to the percentage change of frequency [18].

$$\Delta f_{allow} = f_0 - f_{allow} \text{ is the allowable frequency attenuation.}$$

$$\Delta P_{Secondary\ control\ max} = \sum_{j=1}^m (P_{G_{m,j}} - \Delta P_{primary\ control.j}) \text{ is the maximum amount of secondary control power generated by the power system.}$$

Where, $\sum_{i=1}^{n-1} \Delta P_{Primary\ control} = \sum_{i=1}^{n-1} \frac{-P_{G_{n,i}}}{R_i} \cdot \frac{\Delta f_1}{f_0}$ is the primary control power of the j^{th} generator; $P_{G_{n,i}}$ is the rated power of the i^{th} generator; $\Delta f_1 = f_1 - f_0$ is the frequency attenuation; f_0 is the rated frequency of the power system; $P_{G_{m,j}}$ is the maximum generating power of the secondary frequency control generator j .

2.2. Phase electrical distance and its application in load shedding

The definition of the phase electrical distance (PED) between two buses is defined as in (2)[19], [20]:

$$D_p(i,j) = (J_{P\theta}^{-1})_{ii} + (J_{P\theta}^{-1})_{jj} - (J_{P\theta}^{-1})_{ji} - (J_{P\theta}^{-1})_{ij} \tag{2}$$

As shown in (2) can be written as (3):

$$D_p(i,j) = (J_{P\theta}^{-1})_{jj} - (J_{P\theta}^{-1})_{ij} + (J_{P\theta}^{-1})_{ii} - (J_{P\theta}^{-1})_{ji} \tag{3}$$

where, $(J_{P\theta}^{-1})_{jj} - (J_{P\theta}^{-1})_{ij}$ is the phase angle between 2 nodes j and i due to the power P injected into node j . $(J_{P\theta}^{-1})_{ii} - (J_{P\theta}^{-1})_{ji}$ is the phase angle between 2 nodes i and j due to the power P injected into node i .

As shown in (2) can be written as (4):

$$D_p(i,j) = (J_{P\theta}^{-1})_{jj} - (J_{P\theta}^{-1})_{ji} + (J_{P\theta}^{-1})_{ii} - (J_{P\theta}^{-1})_{ij} \tag{4}$$

where, $(J_{P\theta}^{-1})_{jj} - (J_{P\theta}^{-1})_{ji}$ is the phase angle change at j due to the active power transferred from j to i . $(J_{P\theta}^{-1})_{ii} - (J_{P\theta}^{-1})_{ij}$ is the phase angle change at i due to the active power transferred from i to j .

In power system, the goal is to concentration on the priority of load shedding at nearby the outage generator location. To do this, the idea of the PED between node i and node j is applied. Two nodes that are close to each other will always have a very small PED between them. The smaller PED between the load node and the generator, the closer the load node is to the faulty generator. Therefore, when a fault occurs in an area on the grid, the adjustment of the grid at the faulty area will achieve the best effect. Therefore, minimizing the control error in the faulty area will cause less effect on other areas of the system. In load curtailment, zoning a serious fault and shedding loads around the faulty area will make the impact of the fault on the system smaller, the load shedding plan will be more effective. When a generator failure occurs at node n , the quantity of shedding power at m different load nodes based on PED can be distributed according to the principle: the closer the load node of the failed generator, the greater the amount of shedding power and vice versa. The expression to calculate the load reduction capacity at load nodes according to PED is shown in expression (5) [21]:

$$P_{LSi} = \frac{D_{p,eq}}{D_{p,mi}} \cdot P_{LSmin} \tag{5}$$

with

$$D_{p,eq} = \frac{1}{\sum_{i \neq m} \frac{1}{D_{p,mi}}} \tag{6}$$

In which: m is the quantity of generators; i is quantity of bus; P_{LSi} is the load reduction capacity at i^{th} bus (MW); P_{LSmin} is the minimum load reduction capacity to restore the frequency back to acceptable range (MW); $D_{p,mi}$ is the PED of the load to the failure generator m ; $D_{p,eq}$ phase angle sensitivity of all load buses and generators. The PED between load buses and generator is shown in Figure 1.

2.3. Particle swarm optimization (PSO) algorithm and back-propagation neural network (BPNN)

BPNN proposed by Rumelhart, Hinton and Williams in 1986 is applied in research fields such as pattern recognition, data prediction, problem recognition, image processing and many more other areas [22], [23] based on the ability to self-learn from mistakes. To overcome the disadvantages of BPNN networks, the PSO algorithm is one of the optimal search techniques to help solve the problems posed above. It allows searching for optimal solutions over large spaces.

The PSO algorithm, which modeled the flight of birds in searching for food, was introduced by Kennedy *et al.* [24]. PSO is set with a random group of particles (solutions) and then in processed of finding

optimal solution by updating generations. In each generation, each instance is updated to the two best values. The first value is the best solution obtained so far, called P_{best} . Another optimal solution that this individual follows is the global optimal solution G_{best} , which is the best solution that the individual neighbor of this individual has achieved so far. In other words, each individual in the population updates their position according to its best position and that of the individual in the population up to the present time, which is shown in Figure 2 [24]. The flowchart of the PSO algorithm is shown in Figure 3.

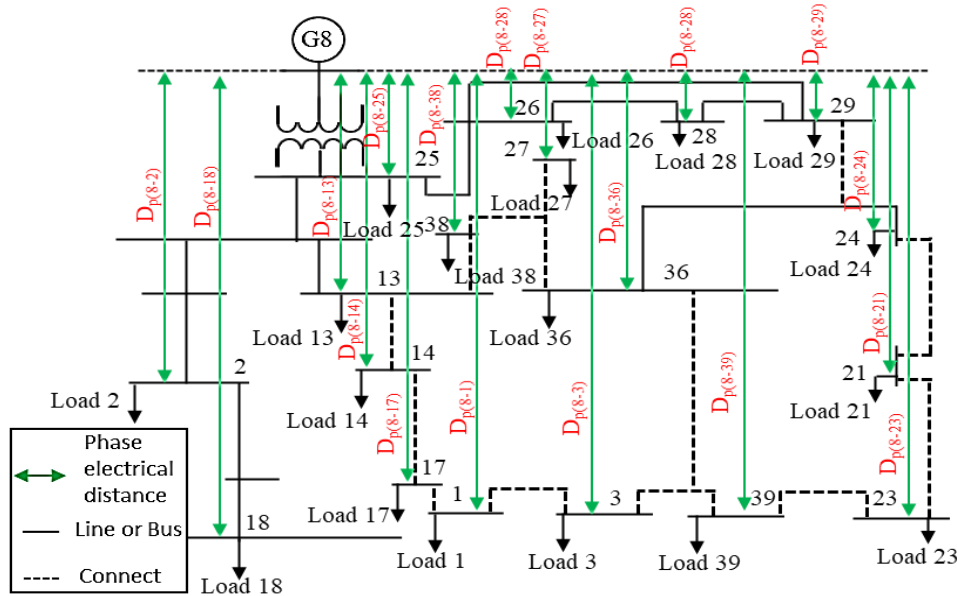


Figure 1. Describe the PED between generator 8 and the load buses

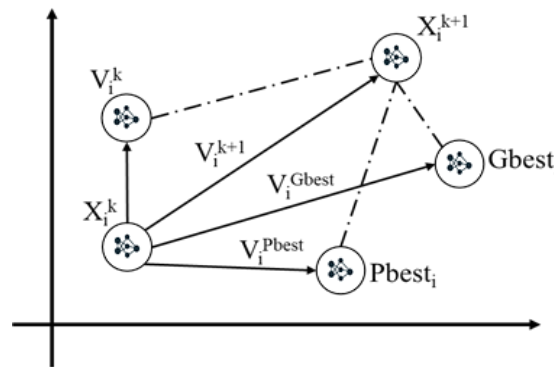


Figure 2. The position of the individuals in the convergence of the PSO algorithm

Velocity and position of each particle is updated as (7):

$$v_i^{k+1} = w \cdot V_i^k + c_1 \cdot r_1 (P_{best} - X_i^k) + c_2 r_2 (G_{best} - X_i^k) \tag{7}$$

After each cycle the location of each instance will be updated as (8):

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{8}$$

In which:

V_i^k, X_i^k : the velocity and position of each particle i at iteration k .

W : inertia weight.

c_1, c_2 : acceleration coefficients, whose range are between 1.5 and 2.5.

r_1, r_2 : random value generated for each velocity update, whose value are in range [0; 1]

P_{best}, G_{best} : the best position of the i^{th} particle, and the best position in the corresponding population, respectively.

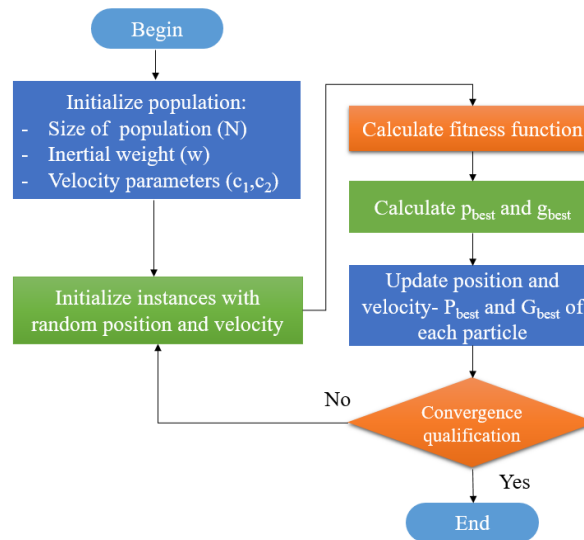


Figure 3. PSO algorithm diagram

3. BUILDING HYBRID ALGORITHM: ARTIFICIAL NEURAL NETWORK-PARTICLE SWARM OPTIMIZATION (ANN-PSO)

The working principle of the hybrid ANN-PSO algorithm is mostly based on the effectiveness of BPNN, which is the adjustment of the weight is always in the descending direction of the error function and requires only some local information. However, the BPNN also has limitations [16] such as low convergence speed and instability. These limitations are due to the fact that the network cannot be trained when the weights are adjusted to very large values. The case of error curves is so complex that there are so many local minima that the convergence of the algorithm is very sensitive to the initial values. Inspired from [25], by combining with PSO, the network training performance can be improved as well as helping the network avoid the "local minima" errors during training. The only limitation of this proposed algorithm is the necessity to set the parameters of the algorithm to match the data. The block scheme of the proposed method is shown in Figure 4. The hybrid artificial neural network-particle swarm optimization (ANN-PSO) algorithm implementation process is presented in Figure 5.

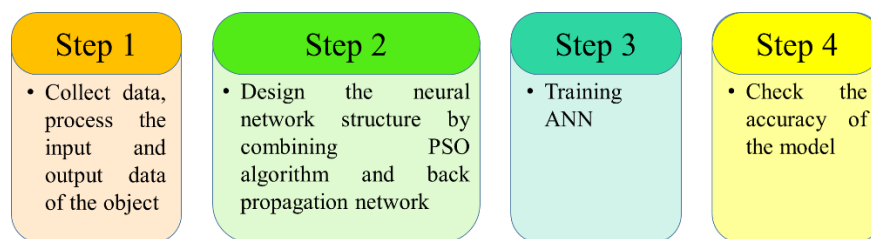


Figure 4. The block diagram of proposed method

The steps to implement the ANN-PSO hybrid algorithm are as:

Step 1: Initialize the network structure with input and output data.

Step 2: Carry out the implementation of the PSO algorithm to find a suitable new W weight for the neural network according to the following objective function:

$$MSE = \frac{1}{n} \sum_{i=1}^n (d_i - y_i)^2 \tag{11}$$

where: d_i : the i^{th} output of the neural network
 y_i : the i^{th} desired output

n : the output number of the neural network

Step 3: From the new weights W in the neural network proceed to train the network.

Step 4: Compare and evaluate the results.

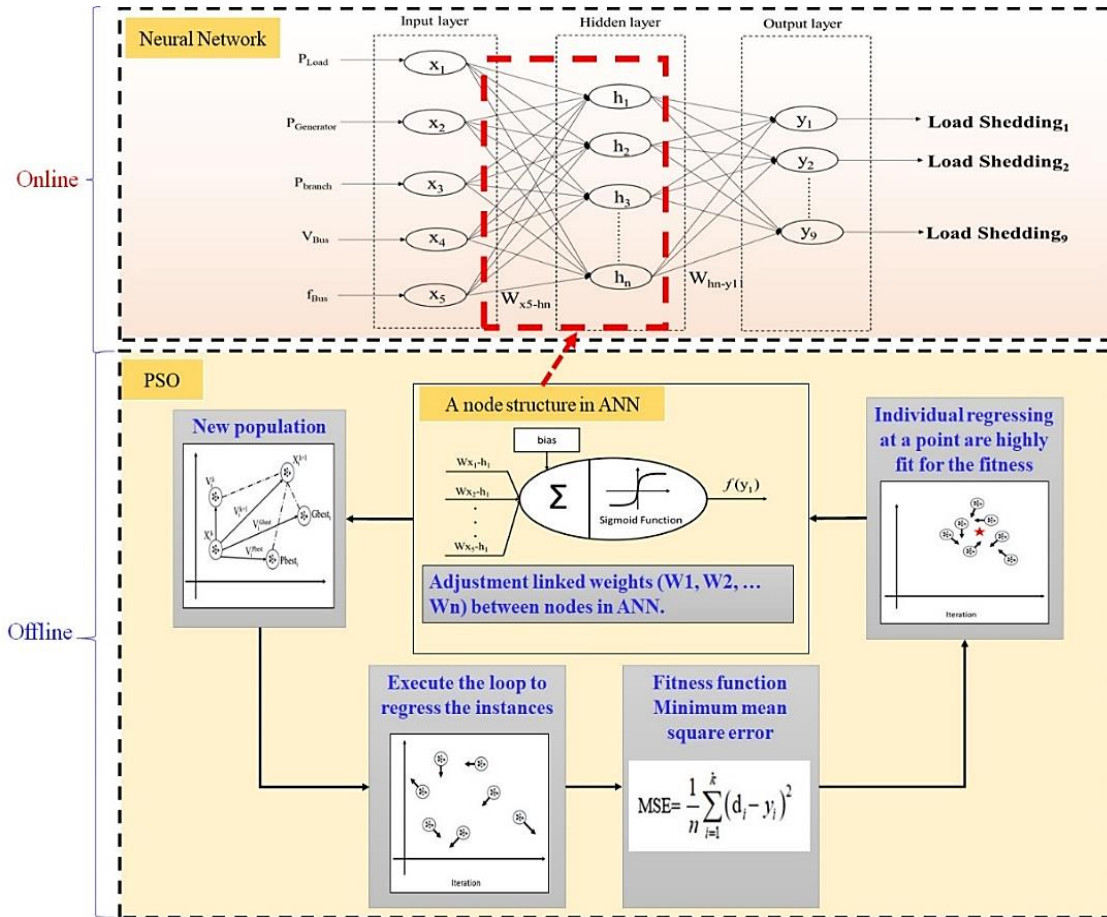


Figure 5. The process of implementing hybrid algorithm ANN-PSO

4. SIMULATION AND RESULTS

The suggested technique is experimented on the IEEE-37 bus with 9 generators and 26 loads bus electrical system [17], [26]. The simulation is processed on the PowerWorld 19. The flowchart of the process of data collection, training and testing is shown in Figure 6.

In this study, the JO345#1 generator (bus 28) disconnected from the power system. Applying the method presented in section 2.1 to estimate the smallest load reduction capacity of 17.64 MW. The PED between the JO345#1 generator and the load nodes is shown in Figure 7.

The simulation results in Figures 8 and 9 show that the proposed load shedding method has an improvement in power quality in terms of frequency bus POPLAR69. After distributed amount of shedding power at each Bus based on PED (mentioned in section 2.2), the frequency increases from 59.6 to 59.7 Hz, which is within allowable range. The proposed load shedding strategy does not have too much impact on voltage quality.

The construction of the training dataset is done by simulating the IEEE 37-bus diagram with varying the loads from 60% to 100% of the maximum load. Each load level will correspond to different generator outage cases. The results obtained in 328 samples, including: 123 samples of load shedding and 205 samples of non-load shedding. For each load shedding case, the delivery of the load reduction capacity at the load buses is made based on the PED, presented in (5) in section 2.2 corresponding to the power level of the load and generator location. Collected data will be normalized and divided into 85% of training, the rest is used to

check the accuracy of ANN-PSO. Proceed to build a training neural network with a network structure of 8 hidden layer neurons with different input variables from 15-165 variables, which are the parameters of the grid system, including: P_{Load} is load active power, generator power is $P_{Generator}$, power on transmission line is P_{Branch} , V_{Bus} is bus voltage, f_{Bus} is bus frequency and the output are 9 variables which are the powers to be shed at the load buses when there is a generator failure from load shedding 1 to Load shedding 9. The accuracy of the proposed method compared with the GA training method and back-propagation is presented in Table 1.

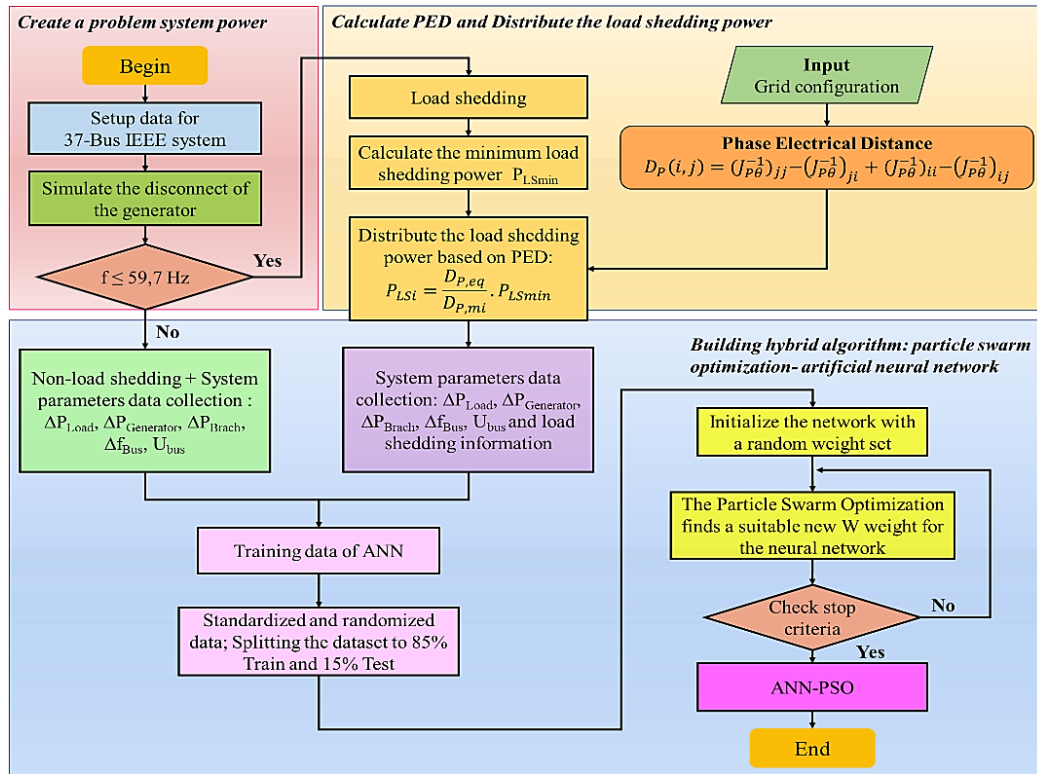


Figure 6. Processing of proposed method flowchart

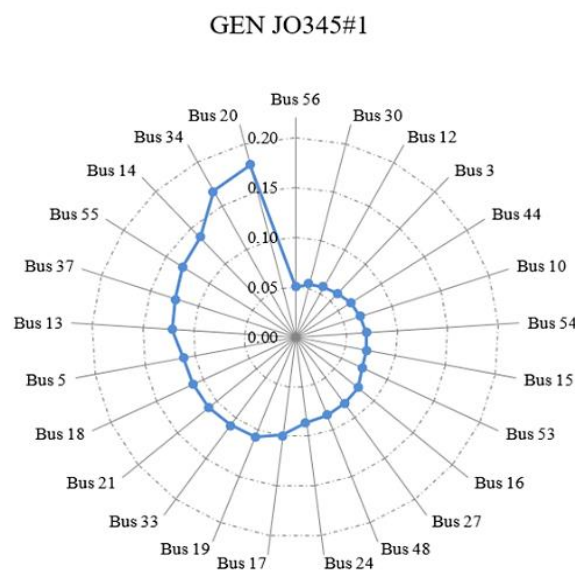


Figure 7. PED relationship between JO345#1 generator and load nodes

The comparison of simulation results between ANN-PSO and GA-ANN methods is shown in Figure 10. Figure 10 presents the simulation results of the proposed ANN-PSO hybrid algorithm applied to the IEEE 37-bus, 9-generator, which has superior advantages over the GA-ANN hybrid algorithm in both time aspects training time and accuracy. Specifically, with 120 input variables, the training and testing accuracy of ANN-PSO is 97.4% and 100% higher than that of GA-ANN at 81.8% and 79.1%. The training time of ANN-PSO is faster than that of GA-PSO hybrid algorithm because the PSO has a faster convergence speed than the GA. Thus, the weight W will be updated faster during training. That shows the effectiveness of the proposed method.

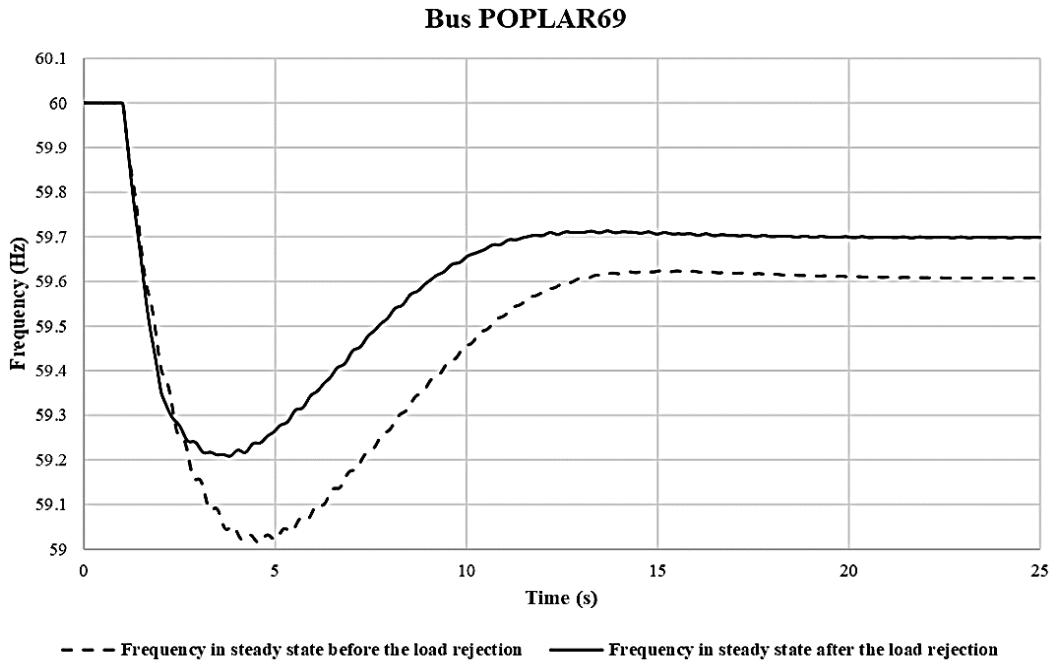


Figure 8. Comparison of frequency bus POPLAR69 between before and after the load rejection

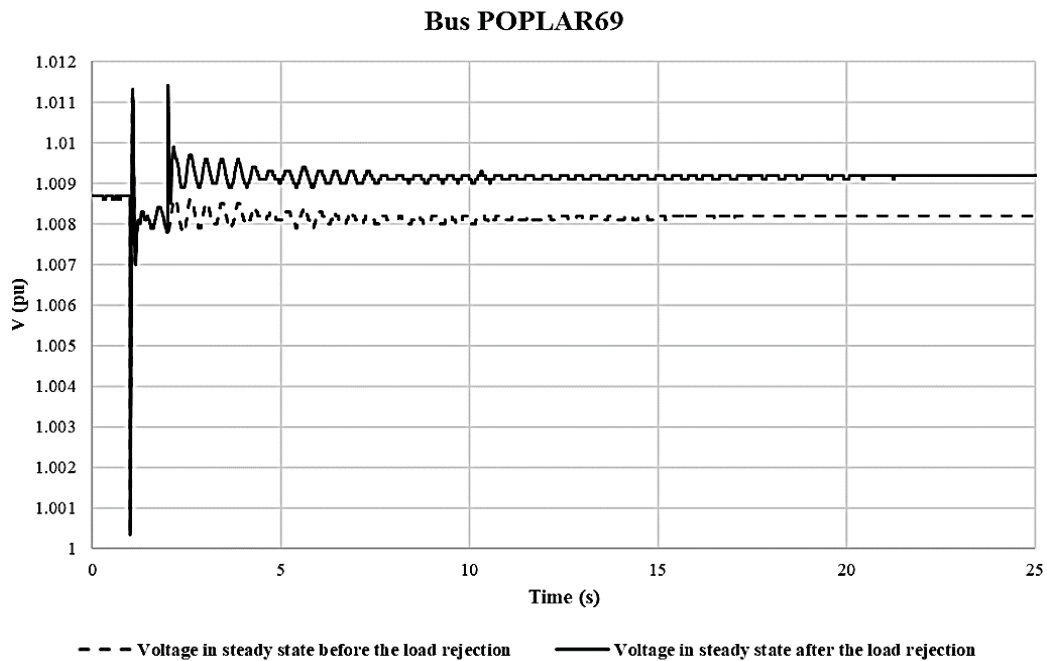


Figure 9. Comparison of voltage bus POPLAR69 between before and after the load rejection

Table 1. Compare the products of the suggested technique with other methods

Variable	ANN-PSO			GA-ANN			BPNN		
	Train	Test	Time_CPU	Train	Test	Time_CPU	Train	Test	Time_CPU
15	96.4	100	2.8	91.1	89.5	542.9	96.4	98.5	1.2
30	90.1	95.5	1.2	97.9	98.5	718.4	90.4	94	1.5
45	90.1	82.1	1.5	84.6	77.6	731.5	90.4	94	2.5
60	90.1	95.5	1.8	83.3	83.6	283.5	94.8	98.5	1.4
75	90.1	82.1	3.1	89.3	85.1	852.1	90.4	94	3.0
90	84.6	77.6	2.9	91.1	89.5	699.6	90.4	94	3.4
105	90.1	82.1	1.9	84.6	77.6	542.2	90.4	94	5.1
120	97.4	100	3.9	81.8	79.1	615.0	90.4	94	2.2
135	91.1	95.5	1.9	80.2	77.6	530.4	90.4	94	2.1
150	97.6	100	2.7	82.03	79.1	1213.8	90.4	94	22.8
165	90.1	82.1	2.6	89.6	85.1	907.0	90.4	94	4.4

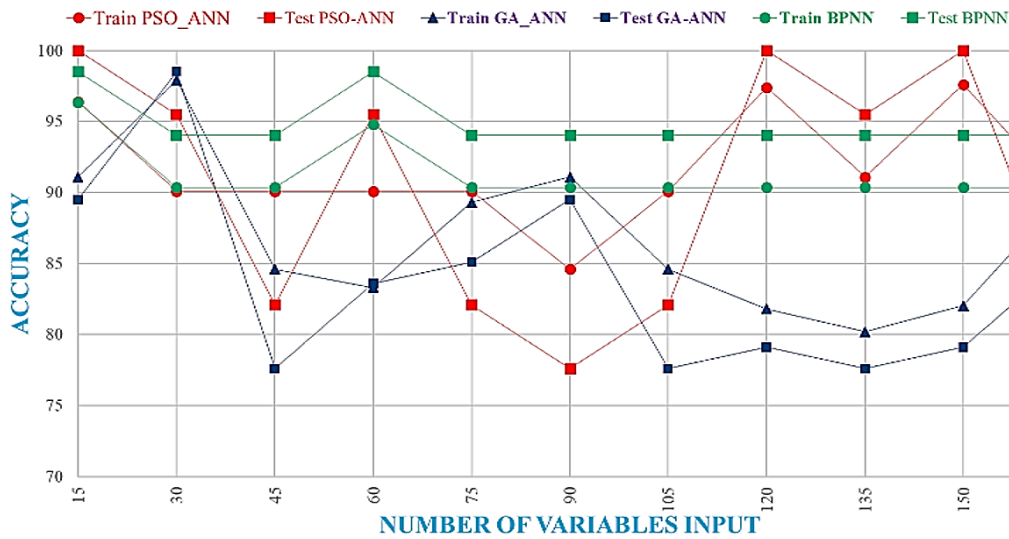


Figure 10. Compare the training results of the proposed method with GA-ANN

5. CONCLUSION

BPNN is a network structure commonly used in identification and prediction problems. BPNN has some drawbacks such as decelerate convergence speed and neighboring minima error, which reduce the performance of the network. PSO is considered as a search algorithm to get the optimal weights in the ANN. The combination of PSO algorithm and neural network with back-propagation algorithm aims to overcome the limitations of the traditional BPNN. The bright result of this method is a network structure can learn faster and predict with better accuracy. The efficiency of the proposed method had been compared with the GA-ANN method to shows the superiority in accuracy and training time.

The optimization in relations of capacity, location and load reduction period takes into account primary and secondary control factors and hybrid ANN-PSO algorithm to establish a rules base which is constructed on the PED applied to the IEEE 37-bus, 9-generator test scheme, the generators have accomplished efficiency in training time just as high precision. In further work, it is needed to consider the impact of renewable energy sources in the analysis of frequency stability and load shedding.

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