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Load Shedding Technique for Power System Using Neural Network Improved by Cuckoo Search Algorithm

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ABSTRACT

The present paper introduces a load shedding methodology that leverages an upgraded neural network that relies on the Cuckoo search (CS) optimization algorithm to compare the efficiency and applicability with other methods in terms of speed and feasibility. The proposed method will be tested on the IEEE-37 bus system. The results of the method are compared with other optimization methods. Thereby, this method gives good results and feasibility in application. The criteria of voltage are considered, specifically the sensitivity index dV/dQ is proposed to find weak buses in the system that need to be relieved of the active power burden. Then, the shedding priority bus ranking is created to ensure the most favorable load shedding plan for the system to maintain voltage stability. Besides, the frequency parameter is also considered to calculate the optimal amount of shed load. The model system was tested by using POWERWORLD software. After comparing the results with other methods outlined in the paper, it has been determined that the proposed approach is highly effective for optimizing grid shedding in the system.

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1. Introduction

As the grid expands, the electrical system is becoming more intricate, making it crucial to verify that the system remains stable and that its parameters fall within acceptable thresholds. There have been many cases where the system instability and grid collapses occur [1]. Some studies on power system voltage collapse have found that large power outages are often caused by more severe events than the design criteria considered [2]. Load Shedding Control System (LSS) is designed to prevent the generators from becoming dangerously overloaded or the entire electric power system from experiencing a complete collapse (blackout) due to generator failure or any unforeseen event that reduces the capacity of operational generators below the power needed to sustain the loads. Besides, the load shedding to ensure the power balance between the source and the load, the frequency is maintained stably within the allowable range [3]. Traditional load shedding methods become ineffective as the electrical grid becomes more complex. Therefore, it is important to conduct research to find out related load shedding methods related to smart algorithms. Many studies are presenting ways to apply intelligent algorithms to automatically shed load. [4]. The purpose of load shedding in the electrical grid is to reduce the load on the grid and maintain the optimal and stable voltage and frequency levels. [5].

In recent years, there have been many studies on the issue of applying intelligent computation methods on the basis of building load shedding strategies. Among them can be mentioned [6]. The authors focus on the challenges faced in maintaining stability in islanded microgrid systems and present various load reduction strategies to address these issues. The evaluation provides a detailed analysis of different configurations of islanded microgrid systems and their impact on backup load shedding plans. In [7], the paper focuses on the deployment and performance evaluation of a frequency-responsive load shedding system for a large industrial facility. The authors describe the design and deployment of the system, using real-time frequency monitoring to automatically trigger load shedding in response to under-frequency events. The paper provides a comprehensive analysis of the system's performance, including the accuracy of under-frequency event detection, the speed and reliability of load shedding response, and the overall effectiveness of the system in maintaining system stability. The authors also provide insights into the technical challenges faced during the deployment of the system and make recommendations for future work in this field. In [8], the authors introduce a new Under Frequency Load Shedding (UFLS) scheme that improves conventional UFLS methods using a continuous load control strategy proportional to frequency deviation. They develop a mathematical model to prove the scheme's effectiveness and evaluate it through simulations, comparing it with conventional methods. While Under-voltage load shedding (UVLS) is a popular cost-effective method to stabilize voltage, it faces difficulties such as determining location, timing, and load shedding value calculation. The conventional UFLS strategy cuts a fixed amount of load corresponding to each frequency setting, depending on expert calculation and simulations. In [9], this study aims to develop a load management system using a swarm optimization algorithm to mitigate under-frequency loads. The proposed system effectively regulates load shedding and improves power system dependability. Compared to Particle Swarm Optimization (PSO), the grasshopper optimization algorithm yields better results. The study concludes that the proposed system is a promising solution for managing under-frequency loads in the power system, offering insights into using swarm optimization algorithms to enhance reliability and stability. In [10], a new approach is proposed by the authors for identifying the best load shedding strategy that employs a combination of a hybrid PSO and ANN. Simulation results show that the proposed method outperforms conventional methods, reducing load shedding and improving system stability. The paper provides a thorough review of existing load reduction methods and a clear explanation of the proposed approach. Overall, this paper offers valuable insights into optimizing load shedding in electrical systems under frequency, and represents a significant contribution to the field.

In order to address the aforementioned issues, it is crucial to compute the ideal quantity of load shedding that is adequate to restore the frequency to an acceptable level following a contingency. After determining the optimal amount of shed load, the distribution of the shedding for each i^{th} bus was calculated based on the Reciprocal Voltage Sensitivity (RVS) in section 2. In section 3, the proposed Artificial Neural Network (ANN) construction is presented to identify the load shedding/no load shedding state, thereby making a decision for the calculation and proposing the shedding strategy. The use of the Cuckoo Search algorithm is to improve the neural network structure to increase the model efficiency.

2. System load shedding program considering frequency and reciprocal voltage sensitivity

The load shedding program applies based on two parameters: frequency and voltage sensitivity at bus, from which the load shedding ratings for each Bus i.

Step 1: Calculate the optimal amount of shed load considering primary and secondary conditions

If there is a power shortage or imbalance between the source and the load, the frequency deviation occurs. To rectify this, frequency control is executed in a particular order: primary control followed by secondary control. If the frequency hasn't been restored to its permissible level even after secondary control, the load is shed. As a result, the proposed formula below is used to calculate the connection between the allowable frequency variation, the quantity of secondary control power, and the minimum power shed P_{LSmin} from loads [11], with:

$$P_{LS\min} = \Delta P_L - \left(\frac{-\Delta f_p}{\beta} \right) - \Delta P_{\text{Secondary}} \tag{1}$$

Where: Δf_p is the amount of frequency change allowed, P_{LSmin} is the minimum power to be load shedding; $\Delta P_{\text{Secondary}}$ is the quantity of power used for secondary control in the system.

Step 2: Calculate Reciprocal Voltage Sensitivity [12] (RVS)

We apply the *dV/dQ* to decide the order of load shedding. The bus with the largest *dV/dQ* magnitude is listed at the top and then sorted in descending order. The equation for voltage sensitivity is:

$$\frac{dQ_i}{dV_i} = 2\left|V_{ii}Y_{ii}\right|\cos(\theta_{ii}) + \sum_{\substack{j=1\\ j\neq i}}^{n}\left|V_jY_{ij}\right|\sin(\delta_{ij}-\theta_{ij}) \tag{2}$$

Where P_i, Q_i is the power entering the i^{th} node; V_i, V_j are the voltages at node i and j; Y_{ij} is the node-sum matrix; δ_{ij} is the phase angle difference of the voltage at i and j; θ_{ij} is the phase angle of the total conductance of segment ij.

The voltage sensitivity of bus i compared to the total voltage sensitivity of the bus [11]:

$$RVS_i = \frac{\dfrac{dV_i}{dQ_i}}{\left(\dfrac{dV_1}{dQ_1} + \dfrac{dV_2}{dQ_2} + \ldots + \dfrac{dV_n}{dQ_n}\right)} \tag{3}$$

Step 3: Calculate the index of the distribution of shedding at the i^{th} bus:

$$S_i = \frac{RVS_i}{\sum_{i=1}^{n} RVS_i} \tag{4}$$

Step 4: The allocation of load shedding to every load bus within the system:

$$P_{LSi} = S_i \times P_{LSmin} \tag{5}$$

3. Improved neural network based on Cuckoo Search algorithm

3.1. Backpropagation neural network

A neural network or an ANN is a set of machine learning models based on the human biological nervous system. The ANN has a basic structure of three main layers [13]. The basic structure of a three-layer neural network is shown in Figure 1 below:

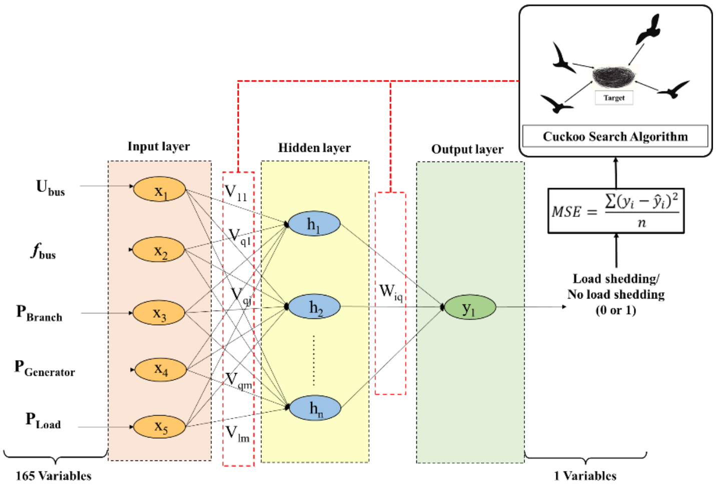

Figure 1. *Artificial neural network structure*

Backpropagation is an algorithm which is applied to Deep Neural Networks. This algorithm gives an efficient and simple solution to calculate the derivative of the objective function with respect to weights and biases at different layers in the network. The note about backpropagation technique is to choose the network architecture such as how many layers and how many nodes are enough to achieve the most efficiency.

The signal processing steps of the back-propagation algorithm to train the 3-layer straight-forward network are as follows:

Step 1: Initialize random weights for the neural network.

Step 2: Feed the input data into the neural network and compute the output value.

Step 3: Compare the computed output value with the actual output value and calculate the loss.

Step 4: Compute the derivative of the loss function with respect to each weight of the neural network by utilizing the chain rule.

Step 5: Update the weights of the neural network using the gradient descent algorithm to minimize the loss.

Step 6: Repeat steps 2-5 multiple times until the value of the loss reaches a small value or does not change much.

Since the weights of the network are updated based on the error signal and can be extended to networks with more computational layers of neurons, the back-propagation algorithm is also known as the generalized Delta learning algorithm.

In Figure 1, instead of calculating the mean squared error after the first cycle, the Cuckoo search algorithm is applied to assist in finding the optimal weights for the neural network structure. This helps the system to escape from local minimum errors and increases the performance of the neural network.

3.2. Cuckoo search algorithm

Inspired by the brood parasitism behavior of cuckoo birds, Cuckoo Search is a metaheuristic optimization algorithm based on swarm intelligence. According to research, Cuckoo Search outperforms other algorithms like GA and PSO in discovering the global optimum of many numerical test functions [14]-[16]. In the CS algorithm, the Levy flight is used, which involves moving in a straight line and then making sudden random turns. By incorporating these characteristics, the CS algorithm enables more effective exploration of the search space compared to other evolutionary computing algorithms [17]. Cuckoo Search has been employed in various optimization problems, including the structural design of wind turbines, vehicle components, and welded structures. Additionally, Cuckoo Search has been proposed for machine learning techniques like Feed Forward Neural Network Training and Document Clustering [18].

The CS algorithm is highly effective for global optimization, making it valuable for machine learning tasks where finding the best solution or model parameters is crucial. Its ability to efficiently explore the search space and potentially discover global optima is advantageous. Furthermore, the CS algorithm's versatility allows it to be applied to various optimization problems, including those in machine learning, whether they involve continuous or discrete variables. Its efficiency in terms of convergence speed is also notable, enabling it to reach optimal or near-optimal solutions within a reasonable number of iterations [19].

The CS process can be easily described in three steps: 1) The nest stores the eggs which symbolize the solution, and it's crucial to note that the cuckoo can only lay a single egg at a given time. 2) Utilizing the Levy flight technique, the cuckoo bird explores to find the most suitable nest, which in this case represents the optimal solution for laying eggs and ensuring the highest possible survival rate. The eggs corresponding to the more optimal solutions will be saved for new generations and the weaker eggs will be discarded. 3) The number of host nests (populations) is fixed. The host bird may notice foreign eggs and these eggs will be discarded or the host bird will leave the nest and build the nest in a new location. If luck is not eliminated, the eggs will grow and become the next generation.

The CS algorithm used in this article applies the Levy Flight move to generate a new value. New values through Levy flight are presented:

$$x_{new} = x + \alpha \oplus \text{Lévy}(\lambda) \tag{6}$$

Where x_{new} is considered the new solution, x is the current solution, $\alpha > 0$ is the step parameter, normally $\alpha = 1$. The Lévy distribution is presented in the formula:

$$\text{Lévy} \sim u = t^{-\lambda}\ (1<\lambda\leq 3) \tag{7}$$

3.3. Problem formulation

In the topic, the research team proposes to improve the backpropagation neural network to improve the neural network structure before training, making it simpler than to train the network and give more accurate results. The Cuckoo Search algorithm is used to search for optimal interconnection weights among neural networks. To achieve this, the fitness function of the algorithm is based on minimizing the mean square error (MSE) of the training function, which is defined as follows:

$$Min(MSE)=\frac{1}{m}\sum_{i=1}^{m}\left(d_i-y_i\right)^2=\frac{1}{m}\sum_{i=1}^{m}\left\{d_i-a_0\left[\sum_{q=1}^{k}w_{iq}a_h\left(\sum_{j=1}^{n}v_{qj}x_j\right)\right]\right\}^2 \quad (8)$$

With m is the number of data samples; d_i is the desired output target; y_i is the predicted result of neural network; a_0 và a_h are activation functions of the neurons; v_{qj} và w_{iq} are the weights of the hidden and output layer neurons; x_j is the input signal of the neural network.

In the article, the values obtained through CS represent the weights of the neural network's connections. These values are limited to the range [-1,1] because the activation function of the weights is the sigmoid function. Consequently, in equation (8), the weight values must be accompanied by the limitation constraint.

$$-1\le v_{qj}\le 1;\ q=1,\ldots,N_1;\ j=1,\ldots,M_1 \quad (9)$$

$$-1\le w_{iq}\le 1;\ q=1,\ldots,N_1;\ i=1,\ldots,M_2 \quad (10)$$

With N_1, M_1 and M_2 are the connections between neurons.

4. Application and Solution

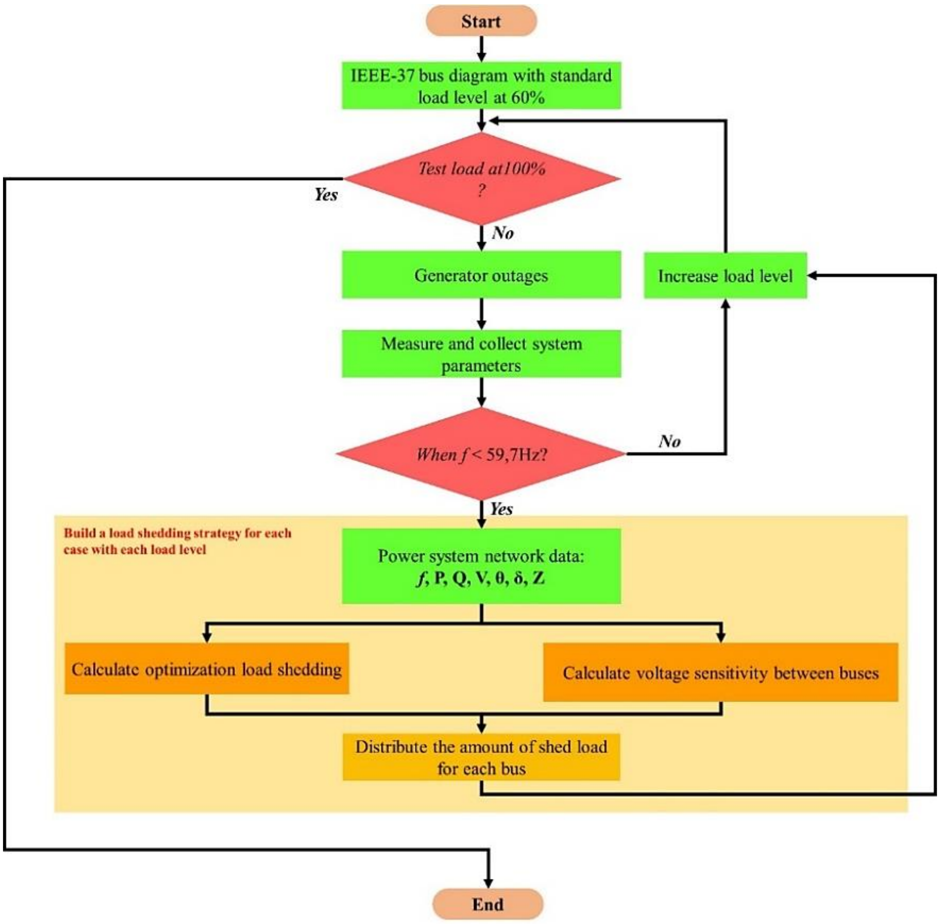

Figure 2. *Flowchart showing incident generation and data collection*

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Testing and evaluating the proposed load shedding model on the sample of IEEE - 37 buses, including 9 generators with parameters of GENCLS type, excitation control model of IEEET1 type, governor model of TGOV1 type, and 26 load buses. The voltage levels on the buses of the diagram from 350kV to 70kV [20]. Simulation is performed on POWERWORLD software, considering generator outages in the power system. The process of fault generation, data collection, and load shedding calculation is presented as a flowchart in Figure 2.

Table 1. *The amount of shed load on each bus*

Bus name	RVS	$S_i = \frac{RVS_i}{\sum_{i=1}^{n} RVS_i}$	$P_{LSi} = S_i \times P_{LSmin}$ (MW)
Bus 3	0.005	0.006	1.044
Bus 5	0.010	0.013	2.118
Bus 10	0.005	0.006	1.013
Bus 12	0.002	0.003	0.534
Bus 13	0.010	0.013	2.182
Bus 14	0.009	0.012	2.013
Bus 15	0.001	0.001	0.219
Bus 16	0.002	0.003	0.432
Bus 17	0.007	0.009	1.481
Bus 18	0.002	0.003	0.436
Bus 19	0.008	0.010	1.706
Bus 20	0.008	0.011	1.854
Bus 21	0.005	0.007	1.154
Bus 24	0.006	0.008	1.372
Bus 27	0.003	0.003	0.547
Bus 30	0.002	0.003	0.482
Bus 33	0.010	0.012	2.093
Bus 34	0.007	0.010	1.637
Bus 37	0.003	0.003	0.548
Bus 44	0.211	0.274	46.075
Bus 48	0.002	0.003	0.524
Bus 50	0.211	0.274	46.075
Bus 53	0.001	0.002	0.301
Bus 54	0.211	0.274	46.075
Bus 55	0.020	0.027	4.460
Bus 56	0.007	0.009	1.479

Figure 2 depicts the process of building a training sample set that is carried out from 60% to 100% load level, each loop is raised to 1%, obtaining 328 data sets or samples including cases with or without shedding. The data structure consists of 5 input signals which are the power of the loads P_L, the power

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of the generators P_G, the transmission power of each line P_B, the voltage V_{Bus} and the frequency f_{Bus} on each bus. The data output is a no load/load shedding signal (0/1).

In case when there is a problem at the ELM345 #1 generator at 60% load, then collect data to consider the shedding/no shedding condition. If the shed process collects system parameters and applies formula (3), we get the RVS index for each i^{th} bus. From that, get the amount of load shedding distributed on each bus based on formulas (4) and (5) as given in Table 1.

Experiments are to be conducted on POWERWORLD software to consider the value improvement of frequency and voltage in the power grid. Figures 3 and Figure 4 show the improved results of the LOCUST69 bus with the frequency increasing from 59.61Hz to 59.87Hz and the voltage value increasing from 0.9947pu to 1.0024pu. The recovery results show that the load shedding distribution contributes to the improvement of frequency recovery, increasing 0.285% over the frequency recovery goal of the optimal shedding calculation.

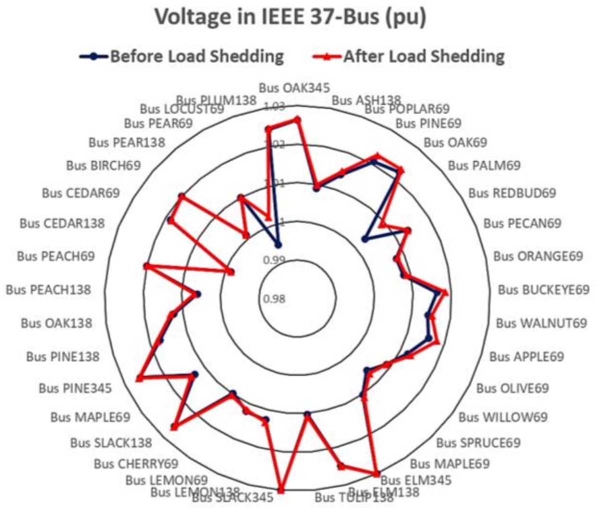

Figure 3. *Voltage values before and after shedding at the buses*

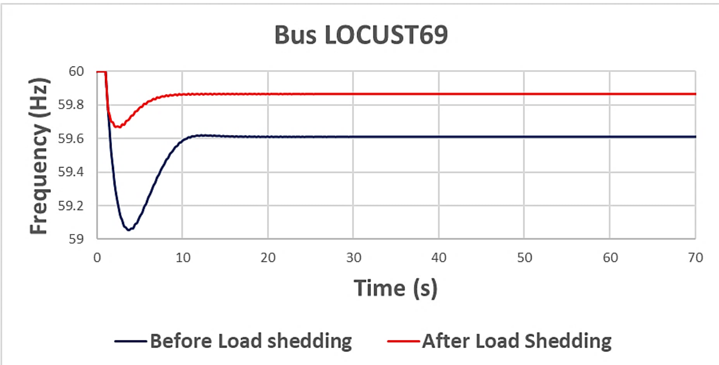

Figure 4. *Frequency values at bus LOCUST69 with 60% load*

The block diagram presenting the operation process of the load shedding model is shown in Figure 5.

Figure 5 shows that when the data building process is completed, it then proceeds to create an improved neural network using the Cuckoo search algorithm. The modeling process includes the following steps:

- **Step 1:** Collect data from the system.
- **Step 2:** Collected data will give the neural network to identify the problem.
- **Step 3:** Calculate the amount of load shedding

- **Step 4:** Conduct load shedding and monitor system.

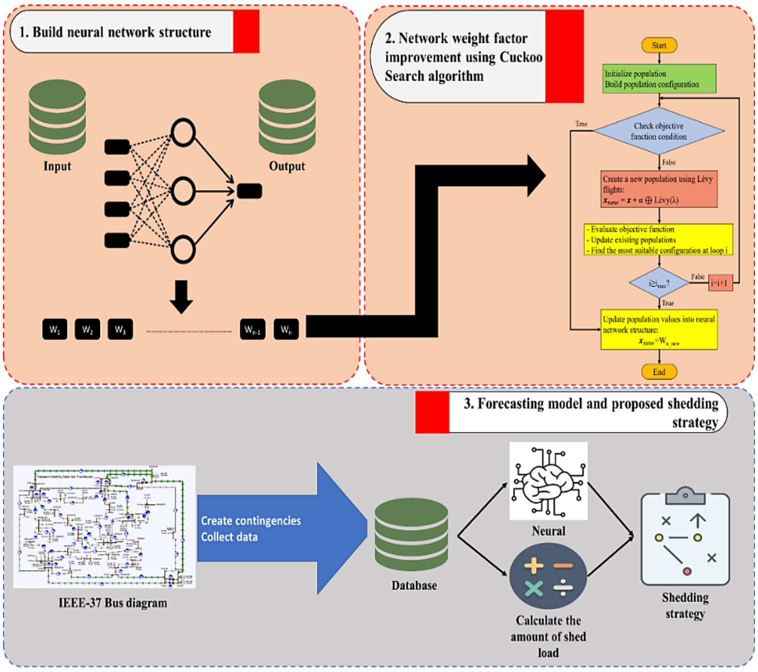

Figure 5. *Block diagram of the proposed model's operation process*

Table 2. *Training accuracy of the proposed neural network with existing methods*

Variables	Proposed ANN			PSO_ANN		
	Train (%)	**Test (%)**	**Time_CPU**	**Train (%)**	**Test (%)**	**Time_CPU**
15	100	100	3.6	96.4	100	2.8
30	100	97.96	2.7	90.1	95.5	1.2
45	99.64	100	10.5	90.1	82.1	1.5
60	99.64	100	4.6	90.1	95.5	1.8
75	100	97.96	6.2	90.1	82.1	3.1
90	100	100	4.5	84.6	77.6	2.9
105	100	100	9.0	90.1	82.1	1.9
120	100	100	14.1	97.4	100	3.9
135	100	100	23.4	91.1	95.5	1.9
150	100	97.96	21.4	97.6	100	2.7
165	100	100	19.9	90.1	82.1	2.6
AVERAGE	99.9	99.4	10.9	91.6	90.2	2.4
Variables	**GA_ANN**			**BPNN**		
	Train (%)	**Test (%)**	**Time_CPU**	**Train (%)**	**Test (%)**	**Time_CPU**
15	91.1	89.5	542.9	96.4	98.5	1.2
30	97.9	98.5	718.4	90.4	94	1.5
45	84.6	77.6	731.5	90.4	94	2.5

60	83.3	83.6	283.5	94.8	98.5	1.4
75	89.3	85.1	852.1	90.4	94	3.0
90	91.1	89.5	699.6	90.4	94	3.4
105	84.6	77.6	542.2	90.4	94	5.1
120	81.8	79.1	615.0	90.4	94	2.2
135	80.2	77.6	530.4	90.4	94	2.1
150	82.03	79.1	1213.8	90.4	94	22.8
165	89.6	85.1	907.0	90.4	94	4.4
AVERAGE	86.9	83.8	694.2	91.3	94.8	4.5

As shown in Figure 6, the results of the accuracy performance of the proposed network outperform other networks. At 150 input variables, the training accuracy of the proposed method is superior to the mentioned methods and is 17.97% higher than the GA-ANN method. The test accuracy is not equal to the PSO-ANN method 2.04% but higher than the GA-ANN method to 18.86%. However, the average accuracy of Cuckoo search - ANN algorithm (99.4%) is much higher than that of PSO-ANN algorithm (90.2%). Although the machine learning time compared with other methods is only faster than the GA-ANN method, the obtained performance is quite superior.

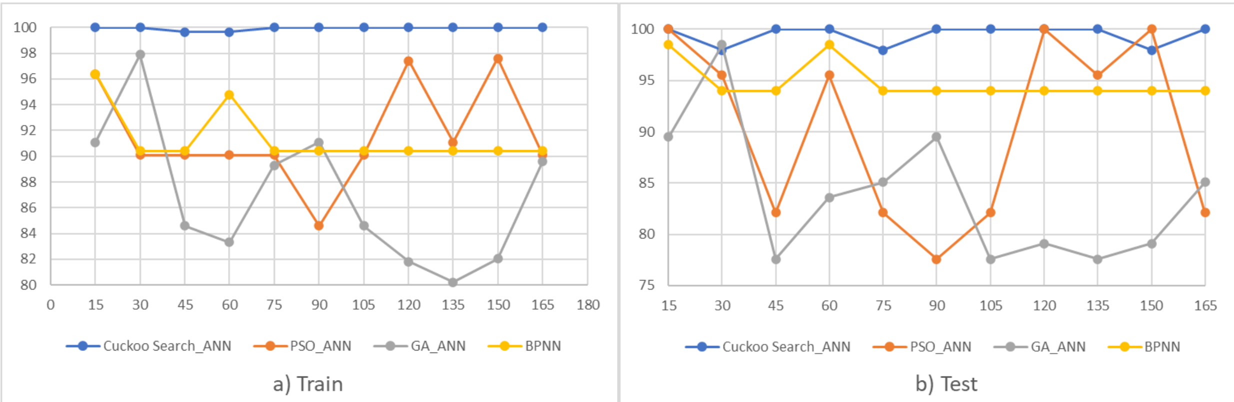

Figure 6. *Comparison chart of the proposed neural network training results*

5. Conclusions

Backpropagation neural networks are very popular in applications such as identification and prediction. However, the network still exist limitations, namely local minima error and experience shortage in parameter selection as well as suitable data processing methods to increase learning efficiency. By utilizing the Cuckoo Search algorithm, the suggested neural network aims to enhance the accuracy of the network by refining the link weights within it. The training results show that although the proposed neural network has no superior learning time, it brings higher accuracy than the previously tested methods.

Optimal load shedding distribution based on Reciprocal Voltage Sensitivity contributes to minimize excessive shedding and inefficiencies. It has economic benefits and avoids the domino phenomenon that the frequency relay shedding method often encounters.

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