A Hybrid Artificial Neural Network - Genetic Algorithm for Load Shedding in Power

Tan T. Phung, Nghia T. Le*, Anh Huy Quyen, Hau H. Pham, and An T. Nguyen

Abstract— *This paper proposes the method of applying Artificial Neural Network (ANN) with Back Propagation (BP) algorithm in combination or hybrid with Genetic Algorithm (GA) to propose load shedding strategies in the power system. The Genetic Algorithm is used to support the training of Back Propagation Neural Networks (BPNN) to improve regression ability, minimize errors and reduce the training time. Based on the control strategies of load shedding consider the primary and secondary control of the generators units, the minimum amount of load shedding was calculated in order to recover the frequency of the power system. The distribution of power load shedding at each load bus of the system based on the phase electrical distance between the outage generator and the load buses. The simulation results have been verified through using MATLAB and PowerWorld software systems. The results show that the Hybrid Gen-Bayesian algorithm (GA-Trainbr) has a remarkable superiority in accuracy as well as training time. The effectiveness of the proposed method is tested on the IEEE 37 bus 9 generators standard system diagram showing the effectiveness of the proposed method.*

Keywords— **Load shedding; Genetic Algorithm (GA); Back Propagation Neural Network (BPNN); Hybrid method; Phase Electrical Distance.**

1. INTRODUCTION

When a large power imbalance occurs in the power system, the frequency will decline rapidly. This problem appears when a generator suddenly outage or increase in load. Before performing load shedding, the monitoring and control system will immediately implement control solutions to maintain the frequency within the allowable range such as: Primary frequency control and secondary frequency control [1]. In case the frequency of the system continues to decrease, the load shedding is the last and the most effective solution. Intelligent load shedding is an optimal method of load shedding using artificial intelligence algorithms to help operators perform load shedding quickly and accurately. The under-frequency load shedding relay (UFLS) [2] is the traditional load shedding method used quite commonly in the current power system. The relays are set to operate whenever the frequency drops to a specified level and a fixed amount of load power is shed to restore the frequency [3]. Using under frequency load shedding relay to disconnect the load bus will result in insufficient or excessive load shedding and take a long time to restore the frequency back to stable [4]-[5]. This result will make damages for the suppliers and customers using the system's power. The combination of Intelligent load shedding methods has also been studied and developed such as Artificial Neural Network (ANN) in load shedding [6], fuzzy logic algorithms [7], genetic algorithm (GA) [8] particle swarm optimization (PSO) algorithm [9]. In recent years, artificial neural networks (ANN) have been used in many different problems such as transformer protection [10] the results obtained for the desired speed and accuracy, ANN gives the least error. However, the shortcoming of ANN in the article is that it is too dependent on the time-consuming training experience to find suitable weights, load forecasting [11]-[12] the proposed short-term load forecast using Artificial Neural Network technology also achieved high accuracy, the neural network in the paper has a basic structure for small errors but is not suitable for predictive problems considering many large data features and sizes, energy management [13]-[14] propose the application of ANN to manage a household's energy by enabling / disabling loads and proposed models that can reduce energy consumption for home appliances at specific times and can be maintaining the total electricity consumption of households below the demand limit, the limitations of the article are limited to small grid and neural network using 2 hidden layers will make the training time longer, electricity price forecast [15] using artificial neural network (ANN) in long-term and short-term electricity price and load forecasting, the proposed model can be used for real-time, online predictions of loads and prices electricity, the limitation of the article is that the neural network structure is not really optimal, the network results do not stick to the real value. In the articles mentioned, ANN is quite popular. However, ANN also has limitations such as network model, network size, activation function, learning parameters, and number of training samples [16]. In the problems of power systems, artificial neural networks often use network types such as Generalized Regression Neural Network (GRNN), Back Propagation Neural Network (BPNN), Hopfield networks and Kohonen networks which are commonly used. In particular, Back

Nghia. T. Le, Tan. T. Phung, Anh. Huy Quyen, Hau. H. Pham, and An. T. Nguyen are with Department of Electrical Engineering, University of Technology and Education 71313, Ho Chi Minh City, Vietnam.

*Corresponding author: Nghia. T. Le; Phone: +84-08-1331-0460; Fax: +84-3-896-4922; Email: trongnghia@hcmute.edu.vn.

Propagation Neural Network (BPNN) is an algorithm that is used effectively to optimize training of Artificial Neural Networks (ANNs). However, the BPNN algorithm has two main disadvantages: low convergence speed and instability. In order to solve the above limits, the Genetic Algorithms (GA) is one of the suitable techniques to overcome.

This paper presents a load shedding method using artificial neural network (ANN) with Back Propagation Neural Network (BPNN) algorithm combine Genetic Algorithms (GA) to support the proposed load shedding strategies for operators' power system of power companies quickly and accurately. The Genetic algorithms (GA) are used to support the training of Artificial Neural Networks (ANNs) to improve the regression ability, minimize errors and reduce training time. Control strategies for load shedding take into account the primary control and secondary control of the generators units to minimize the amount of power load shedding. The phase electrical distance between the outage generator and load buses supports to distribution the amount of load shedding at each load bus. The closer the load bus is to the outage generator position, the greater the amount of power load shedding at that bus. The effectiveness of the proposed load shedding strategy was demonstrated through the test on the IEEE 37 bus – 9 generators system showed the effectiveness of the proposed method.

2. METHODOLOGY

2.1 The power system frequency responds

The response of the load to the frequency difference is represented by the following formula [17]:

$$\Delta P_e = \underbrace{\Delta P_L}_{Nonfrequency-sensitive-load-change} + \underbrace{D\Delta\omega}_{Frequency-sensitive-load-change} \tag{1}$$

where ΔP_L is the load component does not depend on frequency, eg heat load, lighting, ...; $D\Delta\varpi$ is the change in load depends on the change of frequency, eg, motors, pumps, etc; ΔP_e is the deviation of power change; $\Delta\omega_r$ is the deviation of angle speed change; D is the percentage change in load with percentage of change in frequency varies, D is from 1 ÷ 2%.

For the power system has multiple generators with independent governors, the frequency deviation in steady state when the load change is calculated according to the following formula [1].

$$\Delta f = \frac{-\Delta P_L}{\frac{1}{R_1} + \frac{1}{R_2} ... + \frac{1}{R_n} + D} \tag{2}$$

or

$$\Delta f = \frac{-\Delta P_L}{\frac{1}{R_{eq}} + D} \tag{3}$$

where, R_{eq} is the modulation coefficient of the equivalent governor of the whole power system.

$$R_{eq} = \frac{1}{\frac{1}{R_1} + \frac{1}{R_2} + ... + \frac{1}{R_n}} \tag{4}$$

Set $\beta = \left(\frac{1}{R_{eq}} + D\right)^{-1}$ is the general frequency response characteristic of power system. It includes the adjustment characteristics of turbine mechanical power and load. From formula (2), obtain:

$$\Delta f = -\Delta P_L . \beta \tag{5}$$

The effects of the governor speed droop and the frequency of load on the net frequency change are shown in Fig. 1 [18].

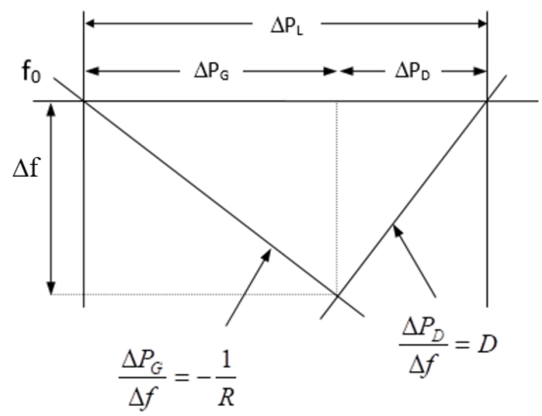

Fig.1. Synthesized frequency response of the power system.

2.2 Calculate the minimum load shedding power considering primary and secondary controls

Primary frequency control is an instantaneous adjustment process performed by a large number of generators with a turbine power control unit according to the frequency variation.

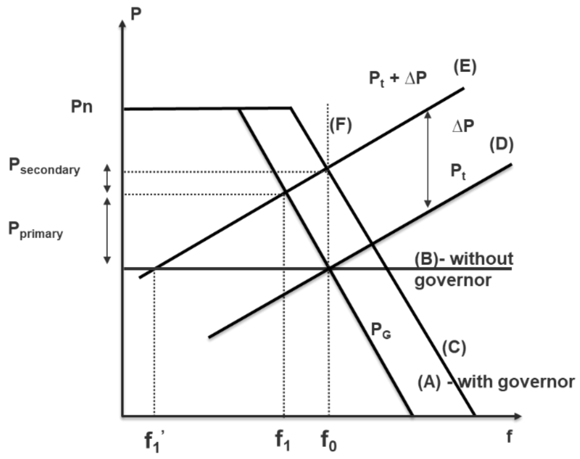

Fig. 2. The relationship between frequency deviation and output power deviation.

Secondary frequency control is the subsequent adjustment of primary frequency control achieved through the AGC's effect (Automatic Generation Control) on a number of units specifically designed to restore the frequency back to its nominal value or otherwise, the frequency-adjusting effects are independent of the governor's response called the secondary frequency control. The process of the primary and secondary frequency control was shown in Fig. 2 [1].

In the case of the power deficiency or imbalance between the source and the load causing the frequency difference, the frequency control will be implemented in the following order: primary control, secondary control. When the reserved power is used for secondary control and the frequency has not been restored to the permitted value, the load will be shed. Thus, from formula (5), the relationship between the permissible change in frequency, the amount of secondary control power and the minimum load shedding power $P_{LS\min}$ is calculated according to the proposed formula below:

$$\Delta f_p = -\beta.[\Delta P_L - (\Delta P_{\text{Secondary control}} + P_{LS\min})] \tag{6}$$

In this case, if ($\Delta P_{\text{Secondary control}} + \Delta P_{LS\ min}$) < $\Delta P_{\text{Secondary max}}$, then ΔP_{LSmin}=0, otherwise the minimum power load shedding is calculated by the formula below:

$$P_{LS\min} = \Delta P_L - \left(\frac{-\Delta f_p}{\beta}\right) - \Delta P_{\text{Secondary Max}} \tag{7}$$

where Δf_p is the permissible change in frequency (pu); P_{LSmin} is the minimum amount of power required to shed (pu); $\Delta P_{\text{Secondary control}}$ is the amount of secondary control power addition to the system.

2.3 Load Shedding Distribution

The phase electrical distance between the outage generator and load buses is calculated using the proposed process in [19], which is performed as follows:

- Calculate the Jacobian matrix from the power flow distribution according to Newton Raphson, and from there obtain the sub matrix J1 with $J_1 = \left[\frac{\partial P}{\partial \delta}\right]$.
- Inverse matrix J1, $J^{-1} = \left[\frac{\partial P}{\partial \delta}\right]^{-1}$.
- Calculate the phase electrical distance between two bus *i* and *j* according to the formula:

$$S_P(i,j) = \frac{\partial \delta_i}{\partial P_i} + \frac{\partial \delta_j}{\partial P_j} - \frac{\partial \delta_i}{\partial P_j} - \frac{\partial \delta_j}{\partial P_i} \tag{8}$$

The general formula calculates the load shedding distribution at nodes according to the phase electrical distance:

$$P_{LSi} = \frac{S_{P,eq}}{S_{P,mi}}.P_{LS\min} \tag{9}$$

where: m is the number of generator bus; i is the number of load bus; P_{LSi} is the amount of load shedding power for the *i* bus (MW); P_{LSmin} is the minimum amount of load shedding power to the restore of frequency back to the allowable value (MW); $S_{P,mi}$ is the phase electrical distance of the load to the m outage generator; $S_{P,eq}$ is the equivalent phase electrical distance of all load buses and generator.

3. HYBRID ALGORITHM BETWEEN GENETICS AND BACK PROPAGATION IN ANN

3.1 Backpropagation neural network (BPNN)

Currently, there are many different ANN training methods, in which Back Propagation Neural Networks (BPNN) are used in research areas such as: sample recognition, data prediction, fault identification, image processing and many other areas. BPNN is a multi-layer neural network model based on Supervised Learning method. It has characteristics such as good learning themselves, powerful self-adaptation and generalization [20].

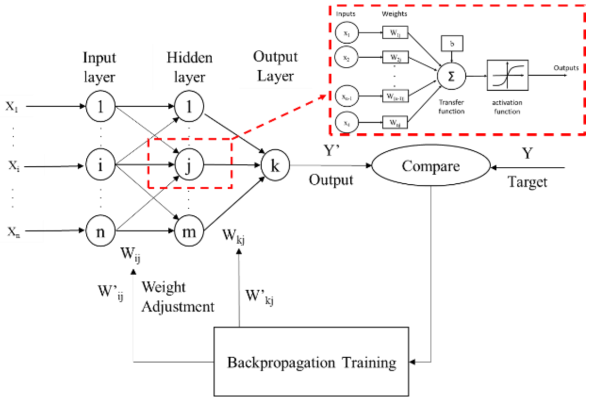

Fig. 3. The structure of Back Propagation Neural Networks (BPNN).

Back propagation used artificial neural networks to calculate a Gradient that is needed in the calculation of the weights to be used in the network. However, the BP algorithm has two main disadvantages: low convergence speed and instability. Those limitations are due to Gradient descent with backpropagation is not guaranteed to find the global minimum of the error function, not only a local minimum; but also, it has trouble crossing plateaus in the error function landscape [21]. However, to solve this problem, Genetic Algorithms are one of the best optimal search techniques to solve the problems above, it allows searching for optimal solutions on large spaces.

3.2 Genetic Algorithms (GA)

The basic principle of genetic algorithm is to simulate natural selection process to solve optimization problems based on Darwin's Theory of Evolution. The genetic algorithm repetitively modifies a population of individual solutions. At each step, the genetic algorithm selects the best individuals at random from the current population to be parents and uses them to produce the children for the next generation. Over generations, the population "evolves" toward an optimal solution. Genetic algorithm is applied to solve a variety of optimization problems that are not well suited for standard optimization algorithms, including problems in which the discontinuous fitness function, no differentiable, stochastic, or highly nonlinear. The genetic algorithm uses three main types of rules at each step to create the next generation from the current population.

- Selection rules individuals, select the best individual pair for creating next generation.
- Crossover rules combine the genetic information from two parents to form children for the next generation.
- Mutation rules, apply random changes to each parent to form the next generation.

3.3 Hybrid genetic algorithm-neural network

Back Propagation adjusts the weights in descending the error function and it just needs some basic information. However, back propagation also has drawbacks such as adjusting complex error functions so it often traps in local minima. It is very inefficient in searching for global minimum of the search space makes the training time longer. GA is parallel random optimization algorithms. Compared to BP, GA is more qualified for neural networks when we consider to search for global. On the other hand, the limitation of GA is the long processing time, mainly due to the random initialization of the population and the use of search mechanisms [22]. From the above analysis, it is easy to get the complementarity between BP and GA.

This section presents a solution for optimizing BPNN by using GA to find the associated weights in the neural network structure to reduce or avoid local minimum errors then use the back-propagation algorithm to train the neural network with the weights found to ensure convergence and achieve the optimal level. Fig. 4 shows the application of the Hybrid Genetic Algorithm – Back Propagation Neural Networks (GA-BPNN) in online and offline models in the power system.

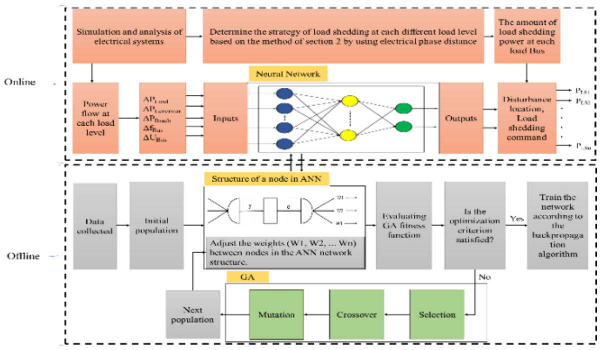

Fig. 4. The offline and online processes of the load shedding using the hybrid GA – BPNN.

ANN will receive the data which collects from simulation the outage generator with different load levels to create a prediction system. This system incorporates in load shedding strategies which are according to the proposed method to recover frequency to allowable values in a short time. The data set used to train neural networks is collected from the IEEE 37 bus 9 generators model in two cases: stable and unstable with 328 sets. The offline process will create ANN by the proposed method to create an identification system which used for the online process.

Offline training process: The simulation process is shown in the flowchart in Fig. 4.

- Step 1: The neural network has a structure of 165 inputs, 2 outputs, with random weights.
- Step 2: Find the weight values in the neural network by genetic algorithm with the minimum fitness function according to the Mean Squared Error (MSE), using the following formula:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - Y_i^{'}) \tag{10}$$

where, n is the number of samples.

- Step 3: Receive neural networks with optimal weights and train by back propagation algorithm.

Online running process: The neural network after being trained with the optimal weights is applied into the online running process to evaluate the effectiveness of recognition system and propose resolve strategies.

The knowledge base of the load shedding system is pre-processed by using input and output databases carefully selected from system studies and simulations in the offline training process. From there, give a specific load shedding strategy for each disturbance, as shown in Fig. 5.

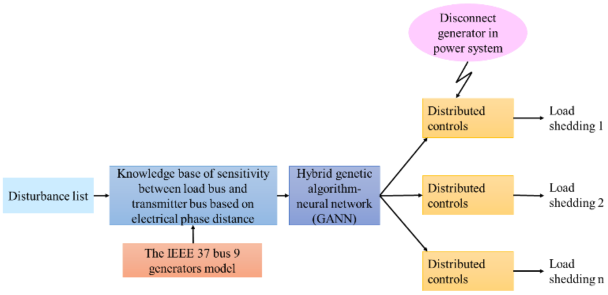

Fig. 5. The function block of intelligent load shedding in power system.

4. SIMULATION AND RESULTS

The IEEE 37 bus standard system diagram is selected as the test system. The single-line diagram of this system is shown in Fig. 6, and the system data are available in [23]. The case has nine generators, 25 loads and 57 branches with SLACK345 generator at Bus 31 is slack bus. It is constructed with three different voltage levels (69 kV, 138 kV and 345 kV), and the system is modelled in per unit. The simulated diagram with multiple load levels from 60% -100% creates a data consisting of 328 sets with 123 sets of unstable status and 205 sets of stable status. This data will be divided into 85% train and 15% test to train ANN to combine genetic algorithms and backpropagation.

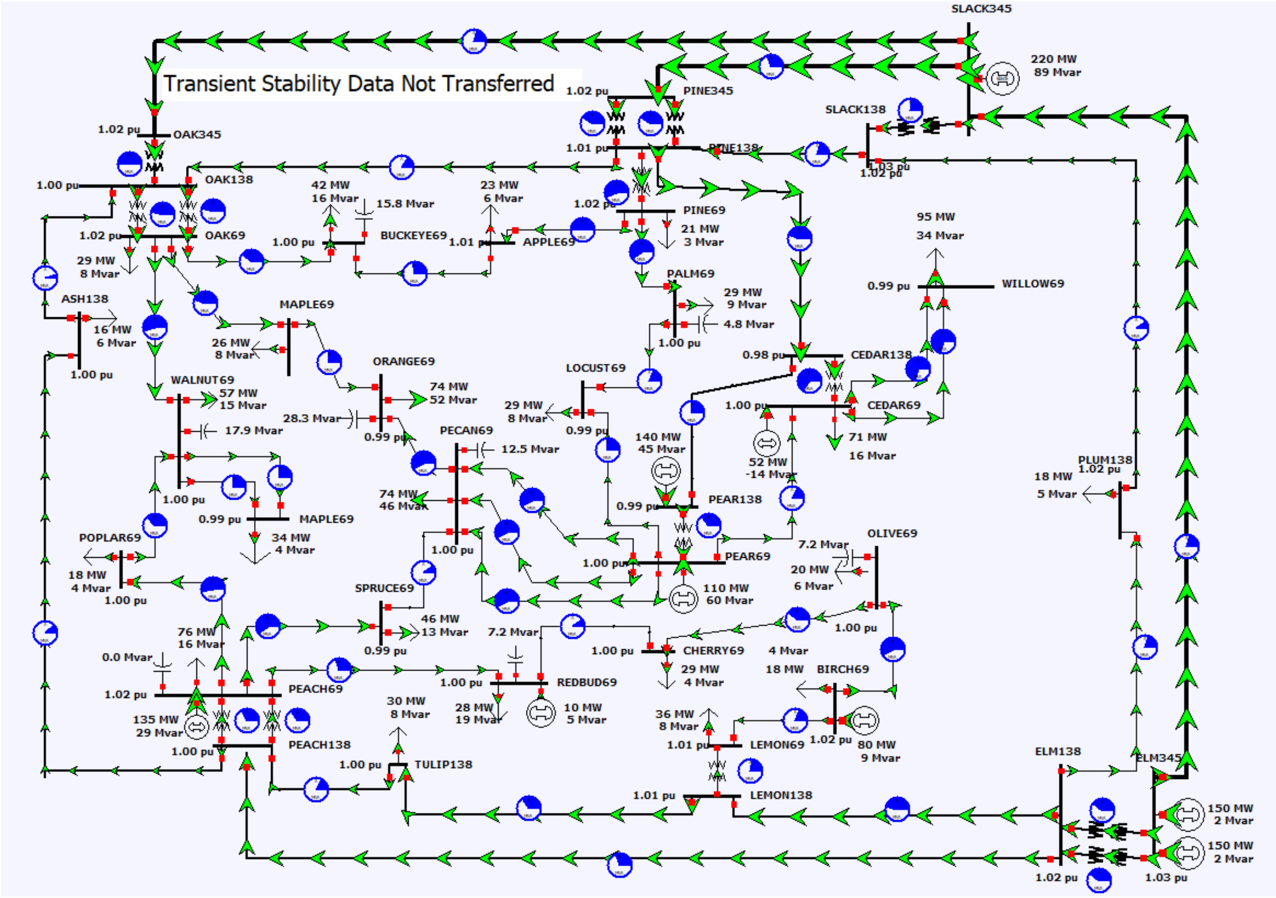

Fig.6. The IEEE 37 bus standard system diagram

4.1. Results of simulation of proposed load shedding method

In the case study, the PEACH69 generator disconnected (Bus 44) from the power system. Applying formula (5) calculated the stable frequency value when the outage generator is 59.62 Hz. Primary and secondary control were implemented afterwards with primary control power of 134.6MW and secondary control power of 18.48MW. The frequency of the power system when the outage generator occurs and after performing primary and secondary controls is shown in Fig. 7.

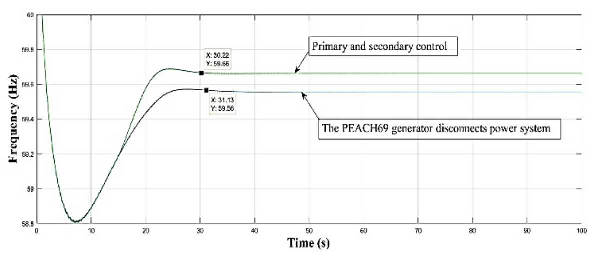

Fig.7. Frequency of the system when the outage generator before and after performing control of the primary - secondary frequency

Table 1. The Load Shedding Distribution at Load Buses

Load Bus	The shedding power at the load buses (MW)
Bus 3	0.631777636
Bus 5	0.510500744
Bus 10	0.426146732
Bus 12	0.605744412
Bus 13	0.269401145
Bus 14	0.412371668
Bus 15	0.541291809
Bus 16	0.463968109
Bus 17	0.335744702
Bus 18	0.397660194
Bus 19	0.302227496
Bus 20	0.24432069
Bus 21	0.318128138
Bus 24	0.541310035
Bus 27	0.449569802
Bus 30	0.661486683
Bus 33	0.342203208
Bus 34	0.281380799
Bus 37	0.349580312
Bus 48	0.415625623
Bus 50	0.247414453
Bus 53	0.457053489
Bus 54	0.525849085
Bus 55	0.260136971
Bus 56	0.419106064

After performing the primary and secondary controls, the system frequency is restored to 59.66 Hz and has not yet reached the allowed value. Therefore, the final solution is load shedding, based on the formula (7) the minimum load shedding power calculated to restore the frequency to the allowable value of 10.41MW. Applying formula (8) and (9), the minimum load shedding power at each bus is shown below the Table 1.

Performing the load shedding according to the proposed method, the restored system frequency value is 59.7Hz and within the allowed value. The frequency of recovery after load shedding is shown in Fig. 8.

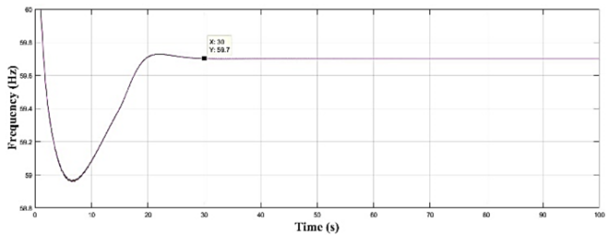

Fig.8. Frequency of the power system after load shedding

4.2. Compare the hybrid GA-BPNN method to traditional methods

In this algorithm, GA is used as an optimal weight generator for BPNN. The weights are coded into chromosomes and evolved by GA. At the end of evolution, the best weights correspond to the best individuals in the selected population as initial weights for BPNN. It is a set of parameters that allows determining the nearest extreme point of the fitness function. With this combination, BPNN will not automatically generate weights but receive weights from GA. The inertial component is removed to increase the speed of the convergence process and to eliminate oscillation during the learning of the Back-Propagation algorithm. Fig. 9 presents a flowchart of the process of developing ANN training data and combining ANN with GA.

The ANN test simulation process is performed with MATLAB software with four training algorithms commonly used in BPNN identification problems: Levenberg – Marquardt (Trainlm), Bayesian regularization (Trainbr), Scaled Conjugate Gradient (Trainscg), Resilient Back propagation (Trainrp). Calculation results and simulations results are presented in Table 2.

Table 2 shows the results of ANN training according to the proposed method compared with the traditional method through 4 training algorithms of BPNN. The comparison results showed that the Gen-Bayesian regularization (GA-Trainbr) has a remarkable superiority in accuracy as well as training time. As with 20 hidden neurons, the improved Bayesian regularization training algorithm reduces CPU training time from 3276,834s to 45,442s and accuracy from 99.617% to 99.894% or Levenberg - Marquardt training algorithm with 2 improved hidden neuron increased accuracy from 86.794% to 99.712%. In the tests, the proposed method uses Bayesian regularization training algorithms combining genetic algorithms (hybrid GA-Trainbr) for the highest efficiency in all hidden neurons.

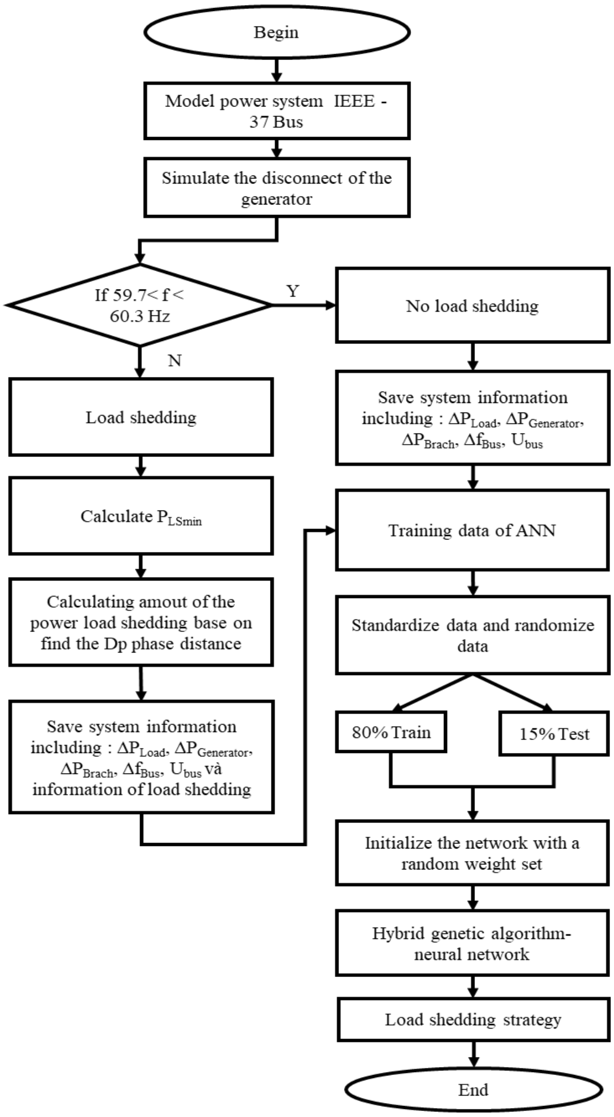

Fig.9. Flowchart hybrid GA-BPNN.

5. CONCLUSION

BPNN is a network structure commonly used in identification and forecasting problems. BPNN with disadvantages such as slow convergence speed and local minimum error reduces network performance. GA is used to optimize BPNN training. The combination of two Gen – Bayesian regularization algorithms (GA - Trainbr) with the idea of taking advantage of this algorithm overcomes the remaining algorithm defects. The result is a network structure capable of learning faster and capable of predicting with better accuracy.

Table 2. Results of the Training Process of the Proposed Method with the Traditional Method

The number of hidden neural	Levenberg – Marquardt				Bayesian regularization			
	Time CPU		*Accuracy (%)*		*Time CPU*		*Accuracy (%)*	
	BPNN	*GA-BPNN*	*BPNN*	*GA-BPNN*	*BPNN*	*GA-BPNN*	*BPNN*	*GA-BPNN*
2	2.875	1.275	86.794	99.712	13.773	1.544	97.832	99.782
4	1.500	0.399	92.057	99.668	27.321	0.701	98.752	99.795
6	4.123	0.874	93.330	99.766	65.978	8.912	93.056	99.976
8	17.695	2.928	92.134	99.776	357.384	13.757	99.610	99.818
10	19.062	2.567	92.185	99.221	647.969	42.353	99.671	99.745
12	12.855	6.902	90.519	99.567	1121.148	55.917	98.994	99.730
14	47.318	14.296	93.586	99.738	1154.992	59.153	99.202	99.976
16	30.295	13.010	92.856	99.742	2048.421	98.678	95.523	99.979
18	25.508	10.771	89.925	99.125	722.287	57.662	99.286	99.965
20	94.816	14.170	94.267	97.913	3276.834	45.442	99.617	99.894
The number of hidden neural	**Scaled Conjugate gradient**				**Resilient Back propagation**			
	Time CPU		*Accuracy (%)*		*Time CPU*		*Accuracy (%)*	
	BPNN	*GA-BPNN*	*BPNN*	*GA-BPNN*	*BPNN*	*GA-BPNN*	*BPNN*	*GA-BPNN*
2	0.160	0.153	86.750	99.799	1.458	0.114	85.311	99.540
4	0.079	0.118	88.749	99.750	0.256	0.072	92.601	99.774
6	0.100	0.178	92.109	99.545	0.247	0.071	79.462	99.680
8	0.160	0.102	92.820	99.407	0.110	0.093	82.987	99.195
10	0.108	0.114	91.552	99.600	0.185	0.089	92.996	99.247
12	0.146	0.197	92.006	99.653	0.135	0.089	94.473	98.849
14	0.106	0.124	81.299	98.760	0.122	0.163	92.092	99.300
16	0.121	0.103	90.975	97.836	0.086	0.120	88.835	99.287
18	0.133	0.111	91.959	99.421	0.085	0.080	89.469	98.108
20	0.112	0.177	88.819	98.387	0.123	0.091	92.161	97.586

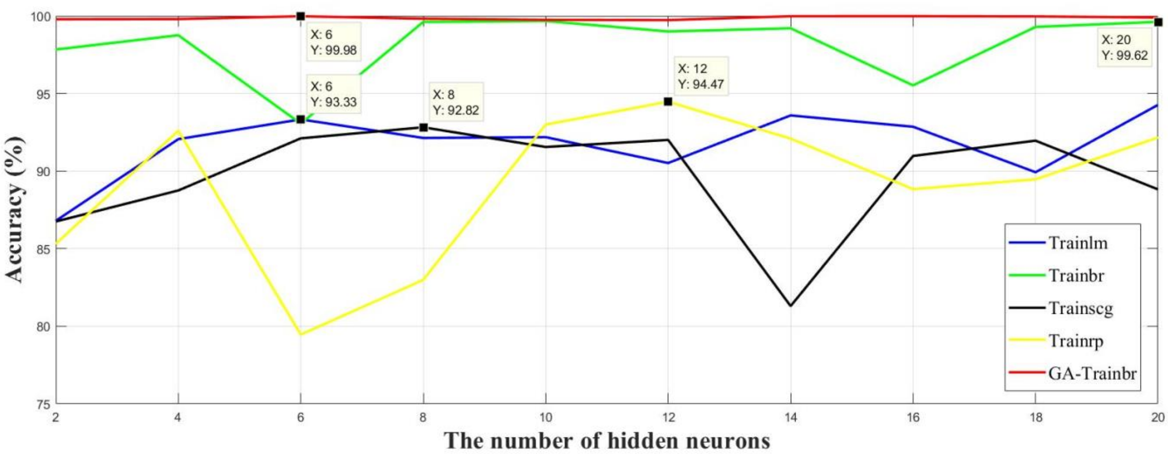

Fig.10. Comparison the hybrid Genetic – Bayesian regularization algorithm (GA-Trainbr) method to traditional methods

The optimal in terms of power, position and load shedding time take into account the primary and the secondary frequency control. The hybrid Genetic – Bayesian regularization algorithm (GA - Trainbr) create knowledge base or rules base which is based on the electrical phase distance to apply to the IEEE 37 bus 9 generators power system standard model, it has achieved training time efficiency as well as high accuracy.

ACKNOWLEDGMENT

This research was supported by the HCMC University of Technology and Education.

REFERENCES

[1] Nghia. T. Le; Anh. Huy. Quyen; Binh. T. T. Phan; An. T. Nguyen; and Hau. H. Pham. 2019. Minimizing Load Shedding in Electricity Networks using the Primary, Secondary Control and the Phase Electrical Distance between Generator and Loads. *International Journal of Advanced Computer Science and Applications (IJACSA)* 10(2): 293-300.

[2] V.V. Terzija. 2006. Adaptive under frequency load shedding based on the magnitude of the disturbance estimation. *IEEE Trans. Power Syst.* 21(3): 1260–1266 August.

[3] Mousa Marzband; Maziar Mirhosseini Moghaddam; Mudathir Funsho Akorede; and Ghazal Khomeyrani. 2016. Adaptive load shedding scheme for frequency stability enhancement in microgrids. *Electric Power Systems Research.* 140. 78-86 June.

[4] S.J. Huang; and C.C. Huang. 2001. Adaptive approach to load shedding including pumped-storage units during underfrequency condition. *IEE Proc.-Gener., Transm. Distrib.* 148(2): 165–170 April.

[5] Y. Halevi; and D. Kottick. 1993. Optimization of load shedding systems. *IEEE Trans. Energy Conv.*. 8(2): 207–213.

[6] C. T. Hsu; M. S. Kang; and C. S. Chen. 2005. Design of Adaptive Load Shedding by Artificial Neural Networks. *IEE Generation, Transmission, Distribution.* 152(3): 415-421 May.

[7] A. A. Sallam; and A. M. Khafaga. 2002. Fuzzy Expert System Using Load Shedding for Voltage Instability Control. *IEEE Large Engineering Con. on Power Engineering*. June.

[8] W. P. Luan; M. R. Irving; and J. S. Daniel. 2002. Genetic Algorithm for Supply Restoration and Optimal Load Shedding in Power System Distribution Networks. *IEE Proceedings - Generation, Transmission and Distribution.* 149(2): 145-151 March.

[9] T. Amraee; B. Mozafari; and A. M. Ranjbar. 2006. An Improved Model for Optimal Under Voltage Load Shedding: Particle Swarm Approach. *2006 IEEE Power India Conference*. April.

[10] B.S.Shah; and S.B.Parmar. 2017. Tranformer protection using artificial neural network. *2017 IJNRD.* 2(5): 108-111 May.

[11] S.M. Elgarhy; M.M. Othman; Adel Taha; and H.M. Hasanien. 2017. Short Term Load Forecasting Using ANN Technique. *2017 Nineteenth International Middle East Power Systems Conference (MEPCON)*. December.

[12] Ricardo Alonso; and Alcides Chávez. 2017. Short term load forecast method using artificial neural network with artificial immune systems. *2017 IEEE URUCON.* October.

[13] S.L. Arun; and M.P. Selvan. 2018. Intelligent Residential Energy Management System for Dynamic Demand Response in Smart Buildings. *IEEE Systems Journal.* 12(2): 1329-1340 June.

[14] Maytham S. Ahmed; Azah Mohamed; Hussain Shareef; Raad Z. Homod; and Jamal Abd Ali. 2016. Artificial neural network based controller for home energy management considering demand response events. *2016 International Conference on Advances in Electrical, Electronic and Systems Engineering (ICAEES).* November.

[15] Dimitrije Kotur; and Mileta Žarković. 2016. Neural network models for electricity prices and loads short and long-term prediction. *2016 4th International Symposium on Environmental Friendly Energies and Applications (EFEA).* September.

[16] Nazri Mohd. Nawi; Abdullah Khan; and Mohammad Zubair Rehman. 2013. A New Back-Propagation Neural Network Optimized with Cuckoo Search Algorithm. *International Conference on Computational Science and Its Applications.* 7971. 413–426.

[17] Allen J. Wood; Bruce F. Wollenberg; and Gerald B. Sheblé. 2014. *Power Generation, Operation and Control*. Third Edition, John Wiley & Sons, Inc..

[18] Prabha Kundur. 1994. *Power System Stability and Control*. First Edition. McGraw-Hill Inc.

[19] L. Patrick. 1990. The different electrical distance. in Proceedings of the Tenth Power Systems Computation Conference, Graz.

[20] Saduf; and Mohd Arif Wani. 2013. Comparative Study of Back Propagation Learning Algorithms for Neural Networks. *International Journal of Advanced Research in Computer Science and Software Engineering.* 3(12): 1151-1156 December.

[21] Yann LeCun; Bengio Yoshua; and Geoffrey Hinton. 2015. Deep learning. *Nature*. 521. 436–444 May.

[22] Philipp Koehn. 1994. Combining Genetic Algorithms and Neural Networks: The Encoding Problem. *The University of Tennessee, Knoxville*. December.

[23] J. D. Glover; M. S. Sarma; and T. J. Overbye. 2017. *Power System Analysis and Design*. Sixth Edition, Cengage Learning. 718.