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ISSN : 2278-0181

International Journal of Engineering Research & Technology

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Load Shedding Apply Neural Network and Voltage Electrical Distance

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Abstract—This paper proposed the method load shedding on the combination of Generalized Regression Neural Network and Voltage Electrical Distance to restore the system frequency to the value within the allowed range. The proposed load shedding method is based on the distance between the generator outage and the remaining nodes to ensure the frequency stability of the system. From there, the loads on the buses which are near the generator outage will be cut firstly, then the next loads until the system return to stable. The effectiveness of the proposed method are tested on the IEEE 39 Bus New England 10 Generators, which demonstrated the effective the proposed method.

Keywords: Load Shedding, Voltage Electrical Distance, Power Sensitivity, Neural Network, Frequency Control.

I. INTRODUCTION

Power system operation always is required to balance the active power and the reactive power between the source and the load. When the balance with the active power occurs, it'll give the serious for the frequency instability of the system. The methods such as reserve the hot standby power of the generation units in the system are only feasible and effective to achieve the above balance when the system is slightly overloaded (frequency of the system less a little). But in cases of serious power imbalance and lead to the blackout completely, the system need be used load shedding program to recovery the frequency.

Jianfeng and et al [1] have developed a method with risk indicators to determine the bus should be targeted for load shedding to maintain stable voltages. Buses with the highest voltages risk are prioritized for load shedding. This is estimated from the probability of the collapse of the voltage occurring. Risk indicators are the products of these probabilities and the effects of voltage collapse.

In [2], Hsu and et al presented a strategy of load shedding by performing artificial neural network (ANN) and transient stability analysis for an electrical system. To prepare the training data for ANN, transient stability analysis of a real power system has been made to address the minimized load with different operating scenarios. The Levenberg-Marquardt algorithm was combined with the back propagation algorithm for neural network training. By choosing the total generating capacity, total load demand and decay frequency are neural inputs of ANN, the output is the minimum number of load

shedding that are identified to maintain the stability of the power system.

In this paper [3], a new approach based on hybrid Particle Swarm-Based-Simulated Annealing Optimization technique (PSO-B-SA) is proposed for solving under-voltage load shedding (UVLS) problem. Under voltage load shedding (UVLS) is one of the most important tools for avoiding voltage instability. In this paper, the UVLS problem is formulated based on the concept of the static voltage stability margin and its sensitivity at the maximum loading point or the collapse point. The voltage stability criterion is modeled directly into the load-shedding scheme. In any UVLS scheme finding the global point is very important for having cost effective economy. The proposed PSO-B-SA methodology is implemented in the under voltage load shedding scheme for IEEE 14 and 118 bus test systems. Simulation results show the efficacy and advantage of the proposed scheme.

A good load shedding program must shed the minimum number of loads as quickly as possible, it also meets all technical constraints to ensure a stable system. Conventional load shedding techniques are limited by load shedding overloading required and slow performance. Intelligent load shedding techniques mostly focus on investigating the timing of load shedding and the amount of load shedding. Studies on the location of load shedding are very limited.

This paper proposed the method of load shedding based on voltage electrical distance method. ANN neural networks are used to identify and classify load shedding control strategies based on the designed rules. The effectiveness of the proposed method has been tested on the IEEE 39 Bus New England.

II. MATERIALS AND METHODS.

A. Generalized regression neural network.

GRNN (Generalized Regression Neural Network) is a basic neural network, is a good tool for calculating approximations in the modeling toolbox. It predicts the output of a given input data.

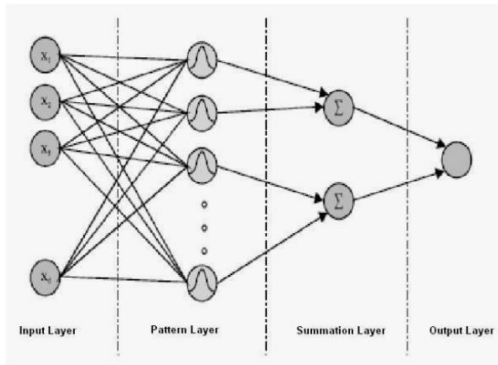


Fig. 1. Generalized regression neural network architecture [4].

Network structure include basic layer 4: input layer, pattern layer, summation layer and output layer. The main advantage of GRNN is to speed up the training process to help the network training faster [5].

B. Voltage electrical distance

Voltage electrical distance between the two nodes i and j is the following formula [6]:

$$D_{(i,j)} = D_{(j,i)} = -\text{Log}(\alpha_{ij} * \alpha_{ji}) \tag{1}$$

Where: $a_{ij} = \frac{\delta V_i / \delta Q_j}{\delta V_j / \delta Q_j}$, $a_{ji} = \frac{\delta V_j / \delta Q_i}{\delta V_i / \delta Q_i}$ (2)

$\frac{\delta V_i}{\delta Q_j}$, $\frac{\delta V_j}{\delta Q_j}$, $\frac{\delta V_j}{\delta Q_i}$, $\frac{\delta V_i}{\delta Q_i}$ are components extracted

from the inverse matrix of the Jacobian matrix.

The formula $\Delta V_i = \alpha_{ij} * \Delta V_j$ [6] represents the voltage drop at node i when disturbance occurs at node j. From formula (1), the distance near found, relative with $D_{(i,j)}$ small or α_{ij} as large. On the other hand, the larger the α_{ij} , the lower the voltage drop at node i when the disturbance at j as large. Thus, when the generator outage, the voltage fluctuation range near the fault node is large, resulting in the voltage drop at near nodes also increases, then load shedding will be at the nearest distance load buses or the largest voltage drop.

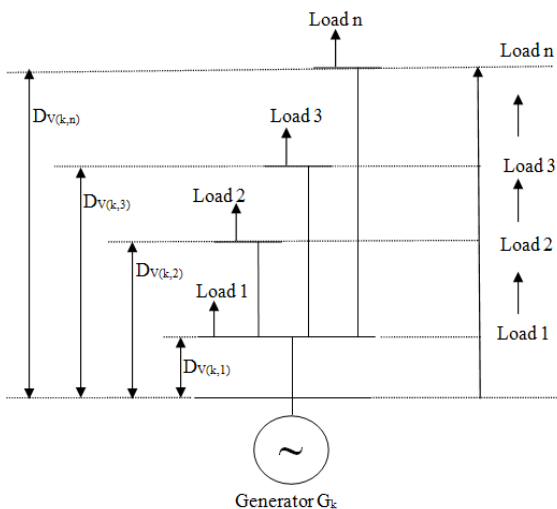


Fig. 2. The block diagram of the relationship between the generator k and the loads

With: $D_{V(k,1)} < D_{V(k,2)} < D_{V(k,3)} < \dots < D_{V(k,n)}$

Prioritized load shedding: Load 1 \rightarrow Load 2 \rightarrow Load 3 \rightarrow ... \rightarrow Load n

III. PROPOSED METHODS

A. Set up load shedding program

Load shedding program are based on three main factors: the timing, the amount of load to be shed and the location of load shedding

The timing: The system data is sent to the control center for continuous measurement, when the system frequency is within the allowable range of $59.7\text{Hz} < f$, the load shedding program will start, the neuron function will be activated to identify the generator outage and the load shedding sequence. The operating time of the UFLS relay is about 0.1s [7] after the frequency falls below the allowable threshold and the process is carried out until the recovery frequency reaches the allowable value. In some emergency cases, (short circuit, loss of generator) this method cannot maintain system stability or restore the frequency with quite long time. Using smart computing technology, the proposed effective load shedding intervals require less than 500ms [8]. Here, the proposed load shedding period is 200ms. This time period includes: measurement of data acquisition, data transfer, data processing and tripping trip. However, to ensure safe margin in real time as well as allowable errors, a period of 100ms [9] is added. So, in the simulation, here the proposed load shedding time is 300ms.

The amount of load to be shed: After obtaining the load shedding sequence list for each generator failure, use the offline PowerWorld simulation software to shed for each generator in trouble at different load levels. (including 21 load levels from 80% to 100%). Dismissed until the frequency of the buses are within the allowable range of stopping, so that for each case the incident will have the number of load shedding corresponding to that case. The incident data collected would correspond to a number of load shedding from the trained neuron function.

Location of load shedding: Use voltage electrical distance for calculating distance between nodes. The load shedding position will be based on the distances from the generator outage (generator bus) to the remaining load buses to the load shedding order, or in other words the priority of the nodes closer to the generator will be first off, because these load nodes directly affect the generator is the most trouble.

The flowchart load shedding process is shown in Fig. 3.

B. Application ANN to identify the failure.

Due to the complexity of the power system, the above-mentioned traditional methods take a lot of time to clear up, thus causing delays in decision making, The ANN method is used to solve difficult problems that traditional methods do not solve in terms of speed and performance.

However, ANN needs to be trained (learned) on the basis of initial data. Therefore, it is necessary to build the set to learn, including various outages. Data samples representing in each outage are the change in generator power ΔP_G , the change of frequency in buses Δf_{bus} , the voltage drop of buses ΔV_{bus} , the change of load ΔP_{load} and the change of power distribution across the transmission lines ΔP_{branch} . During the

simulation, various load levels were considered to cover the operating modes.

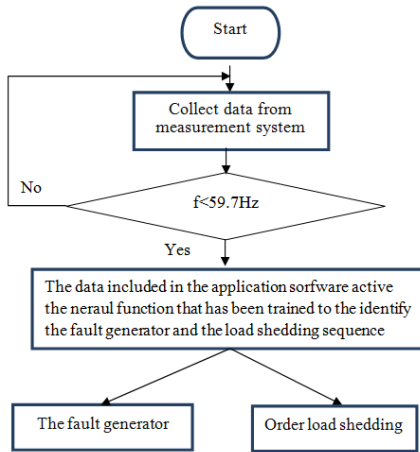


Fig. 3. Flowchart load shedding online

During the ANN model identification process, the creation database of the generator outage is considered the most important. Reliable databases not only determine the accuracy of the assessment, but also have a significant impact on the robustness of the model.

There are two elements that need to be clearly demonstrated during the simulation:

- The database must cover the operational status and must adequately represent the various incident scenarios.
- The generated database must ensure the objectivity of the parameters of the test power system.

The process of creating a database based on simulation PowerWorld and is done through the following 5 stages:

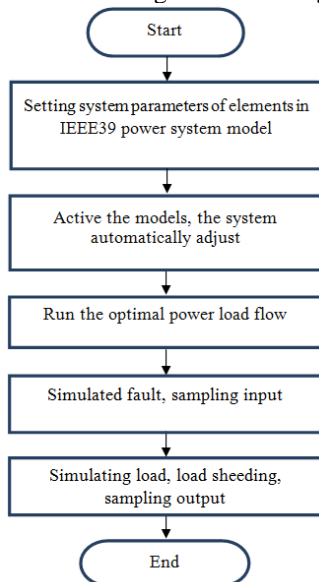


Fig. 4. Simulation steps for input, output sampling

Simulated fault, sample input is shown in Figure 5.

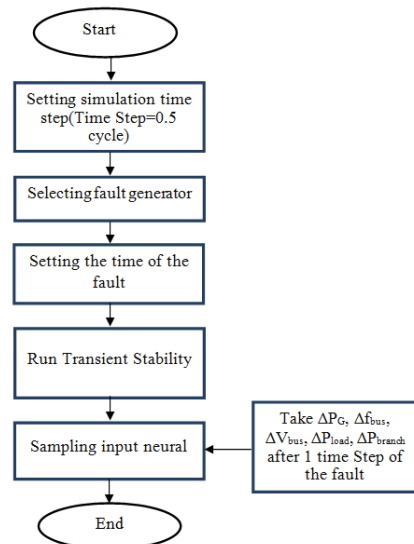


Fig. 5. Simulated fault, neural input sampling

Simulated fault, sample output is shown in Figure 6.

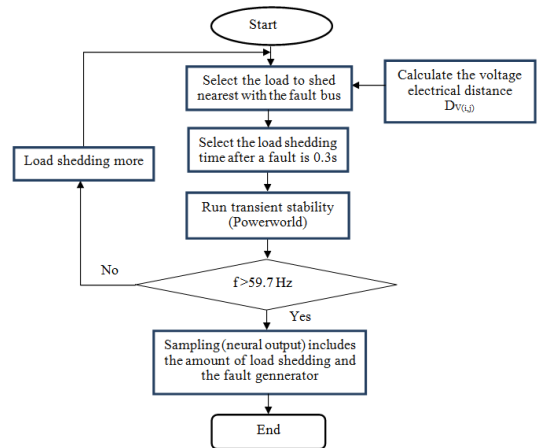


Fig. 6. Simulated load shedding, neural input sampling

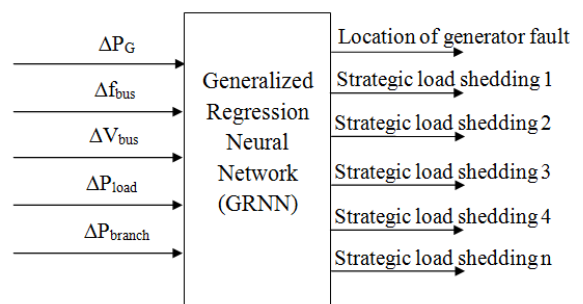


Fig. 7. Neural network training model with inputs and outputs

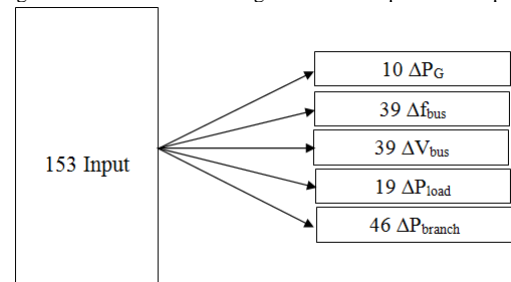


Fig. 8. Input data of the neural network

IV. TESTING ON THE IEEE 39 BUS NEW ENGLAND

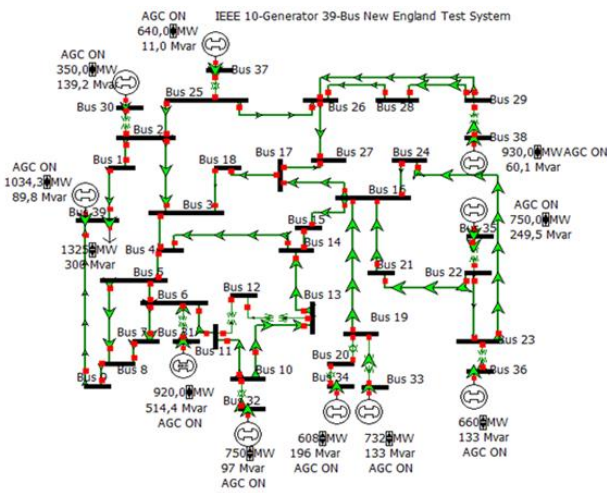


Fig. 9. The IEEE 39 bus New England

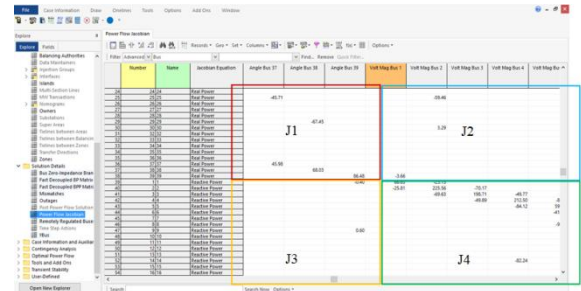


Fig. 11. The Jacobian matrix

Step 3: Inverse J4, call B = J4⁻¹. Each element of matrix B is written:

$$b_{ij} = \left[\frac{\partial V_i}{\partial Q_j} \right] \tag{4}$$

Step 4: Take the α_{ij} decrease matrix, between nodes i and j, as follows:

$$\alpha_{ij} = \frac{b_{ij}}{b_{jj}} \tag{5}$$

$$\alpha_{ji} = \frac{b_{ij}}{b_{ii}} \tag{6}$$

Step 5: Calculate the voltage electrical distance between nodes i and j calculated according to the formula (1):

$$D_{ij} = D_{ji} = -\log(\alpha_{ij}\alpha_{ji})$$

After completing step 5, we obtain table 1

TABLE 1. Table voltage electrical distance between the generator buses and the load buses.

	Bus 30	Bus 32	Bus 33	Bus 34	Bus 35	Bus 36	Bus 37	Bus 38	Bus 39
Bus 3	0.2713	0.6145	0.5104	0.6583	0.4860	0.5908	0.3627	0.5117	0.4162
Bus 4	0.4117	0.4983	0.5665	0.7144	0.5421	0.6469	0.4949	0.6263	0.4479
Bus 7	0.5514	0.5471	0.7253	0.8732	0.7009	0.8057	0.6386	0.7783	0.4446
Bus 8	0.5339	0.5491	0.7153	0.8631	0.6909	0.7957	0.6221	0.7643	0.4053
Bus 12	0.7925	0.6192	0.9137	1.0615	0.8893	0.9940	0.8725	0.9968	0.7824
Bus 15	0.4517	0.6132	0.4053	0.5531	0.3809	0.4856	0.5106	0.5905	0.5427
Bus 16	0.4124	0.6393	0.3183	0.4662	0.2939	0.3987	0.4651	0.5323	0.5243
Bus 18	0.3432	0.6505	0.4561	0.6039	0.4317	0.5364	0.4074	0.4983	0.4790
Bus 20	0.7244	0.9513	0.2636	0.1542	0.6059	0.7107	0.7771	0.8443	0.8363
Bus 21	0.5188	0.7458	0.4248	0.5726	0.2317	0.3679	0.5716	0.6387	0.6308
Bus 23	0.5941	0.8210	0.5000	0.6479	0.2020	0.2170	0.6468	0.7140	0.7060
Bus 24	0.4657	0.6926	0.3716	0.5194	0.3064	0.3967	0.5184	0.5855	0.5776
Bus 25	0.2592	0.7422	0.6092	0.7571	0.5848	0.6896	0.1742	0.4549	0.4567
Bus 26	0.3793	0.7671	0.5769	0.7247	0.5525	0.6573	0.3553	0.2737	0.5449
Bus 27	0.3901	0.7334	0.5179	0.6658	0.4936	0.5983	0.3963	0.3713	0.5405
Bus 28	0.5605	0.9483	0.7581	0.9059	0.7337	0.8384	0.5365	0.1557	0.7261
Bus 29	0.5702	0.9580	0.7678	0.9156	0.7434	0.8482	0.5462	0.0828	0.7359
Bus 39	0.5220	0.8264	0.8426	0.9905	0.8182	0.9230	0.6309	0.8187	0.0000

From Table 1, we build the order of load shedding for each of the generator outage following in Table 2.

TABLE 2. Proposed load shedding strategy

Bus \ Order	Bus 30	Bus 32	Bus 33	Bus 34	Bus 35	Bus 36	Bus 37	Bus 38	Bus 39
1	Load 25	Load 4	Load 20	Load 20	Load 23	Load 23	Load 25	Load 29	Load 39
2	Load 3	Load 7	Load 16	Load 16	Load 21	Load 21	Load 26	Load 28	Load 8
3	Load 18	Load 8	Load 24	Load 24	Load 16	Load 24	Load 3	Load 26	Load 3
4	Load 26	Load 15	Load 15	Load 15	Load 15	Load 16	Load 27	Load 27	Load 7
5	Load 27	Load 3	Load 21	Load 21	Load 15	Load 15	Load 18	Load 25	Load 4
6	Load 4	Load 12	Load 18	Load 18	Load 18	Load 18	Load 16	Load 18	Load 25
7	Load 16	Load 16	Load 23	Load 23	Load 3	Load 3	Load 4	Load 3	Load 18
8	Load 15	Load 18	Load 3	Load 3	Load 27	Load 27	Load 15	Load 16	Load 16
9	Load 24	Load 24	Load 27	Load 27	Load 4	Load 4	Load 24	Load 24	Load 27
10	Load 21	Load 27	Load 4	Load 4	Load 26	Load 26	Load 28	Load 15	Load 15
11	Load 39	Load 25	Load 26	Load 26	Load 25	Load 25	Load 29	Load 4	Load 26
12	Load 8	Load 21	Load 25	Load 25	Load 20	Load 20	Load 21	Load 21	Load 24
13	Load 7	Load 26	Load 8	Load 8	Load 8	Load 8	Load 8	Load 23	Load 21
14	Load 28	Load 23	Load 7	Load 7	Load 7	Load 7	Load 39	Load 8	Load 23
15	Load 29	Load 39	Load 28	Load 28	Load 28	Load 28	Load 7	Load 7	Load 28
16	Load 23	Load 28	Load 29	Load 29	Load 29	Load 29	Load 23	Load 39	Load 29
17	Load 20	Load 20	Load 39	Load 39	Load 39	Load 39	Load 20	Load 20	Load 12
18	Load 12	Load 29	Load 12	Load 12	Load 12	Load 12	Load 12	Load 12	Load 20

The proposed method is tested on The IEEE 39 bus New England, using Powerworld software to collect samples and Matlab software for neural network training.

A. Process created a load shedding program

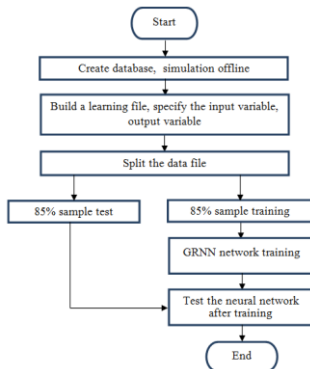


Fig. 10. Flowchart simulator sampling and neural network training

The process created a load shedding program use the neural network shown in Figure 10.

B. Create fault database.

Data is available when each generator outage occurs at different load levels (80% to 100%). This process is done by off-line simulation using PowerWorld software.

Parameters representing in each case of generator faults are the change of generator power (ΔP_G), the change of frequency at the bus (Δf_{bus}), the voltage drop at the bus (ΔV_{bus}), the change in load capacity (ΔP_{load}) and the change in power distribution across transmission lines (ΔP_{branch}).

C. Calculate the phase electrical distance.

Voltage electrical distance is physical relationship between two buses in power system. Voltage electrical distance can be obtained by following step.

Step 1: Turning all PV generator buses into PQ load buses.

Step 2: From the matrix Jacobian J, have a matrix J4 from Powerworld, in which $J4 = [\partial Q / \partial V]$ (3)

Explanation: According to the suggested strategy table above, if there is a fault at generator 30, the load shedding order will be Load 25 → Load 3 → Load 18 → ... until the system is stabilized again. Similarly, for the remaining generators.

D. Build a learning sample set, identify the input variable, output variable.

The number of sample data received via off-line simulation total plus 189 samples (including 21 load from 80% to 100%, per each level have 9 case with 9 generators fault).

Building a learning template is a file under [samples x variables]. The samples are rows, and variables are columns.

Samples data in the learning template under the vector include the variables to the ΔP_G (10), Δf_{bus} (39), ΔV_{bus} (39), ΔP_{load} (19) và ΔP_{branch} (46).

Total the into variables to x are $153 = (10 + 39 + 39 + 19 + 46)$
 $x = [\Delta P_G \ \Delta f_{bus} \ \Delta V_{bus} \ \Delta P_{load} \ \Delta P_{branch}]$

Output variables y is assigned as following: $y = [y1 \ CL1 \ CL2 \ CL3 \ CL4 \dots \ CLn] = 13$

where: y1 is number of generator fault, CLn is strategic load shedding n

Total results of the strategic load shedding on the table 3

TABLE 3. Load shedding strategy for each generator fault

Strategic shedding	Load shedding
Strategic 1 (CL1)	L25
Strategic 2 (CL2)	L25, L3
Strategic 3 (CL3)	L4, L7
Strategic 4 (CL4)	L4, L7, L8
Strategic 5 (CL5)	L20
Strategic 6 (CL6)	L20, L16
Strategic 7 (CL7)	L23, L21, L16
Strategic 8 (CL8)	L23, L21, L24
Strategic 9 (CL9)	L25, L26, L3
Strategic 10 (CL10)	L25, L26, L3, L27
Strategic 11 (CL11)	L29, L28, 26, L27
Strategic 12 (CL12)	L39

E. Split the data file

Data consists of 189 samples and split into two subsets: training data and test data. Training data covers all generator faults at various load levels as well as covers all strategies load shedding when the generator faults.

Training data is 85% of the samples (162 samples), test data is 15% of the samples (27 samples).

F. Neural network training and evaluation.

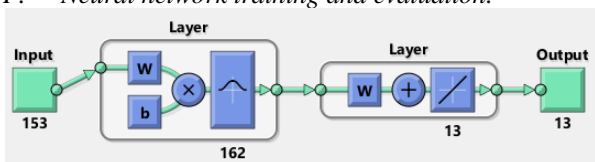


Fig. 12. Neural network training structure

After training, we tested to evaluate the accuracy after training through 27 samples (15%) untrained, resulting in Table 4.

TABLE 4. Evaluate accuracy after neural training

Order	Output variable	Total test sample	Right sample	Wrong sample	Right ratio
1	y1	27	27	0	100%
2	CL1	27	27	0	100%
3	CL2	27	27	0	100%
4	CL3	27	27	0	100%
5	CL4	27	27	0	100%
6	CL5	27	26	0	100%
7	CL6	27	26	0	100%
8	CL7	27	27	0	100%
9	CL8	27	27	0	100%
10	CL9	27	26	0	100%
11	CL10	27	26	0	100%
12	CL11	27	27	0	100%
13	CL12	27	27	0	100%
Average					100%

G. Test load shedding on the IEEE 39 bus New England by Powerworld.

Process simulation sampling with the IEEE 10 generators 39 bus are made as follows:

Assuming the generator outage is 34, at load level 100%, the frequency and deviation of the rotor angle become unstable.

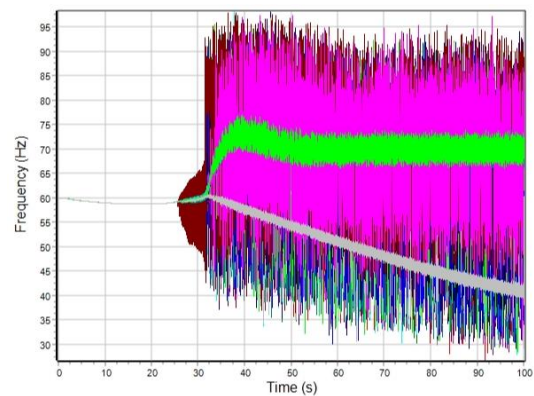


Fig. 13. Diagram of frequency of system at fault generator 34 load level 100% When implementing the proposed method, just load shedding the load on bus 20, the frequency has stabilized.

V. COMPARISON OF METHODOLOGY SUGGESTED WITH OTHER METHODS.

A. Load shedding based on under frequency load shedding relays [10].

Load shedding based on under frequency load shedding relays is the most commonly used method, which is still being used in many parts of the world, including Vietnam. When the grid frequency falls below the permitted threshold, the relay will be load shedding, prevents the system frequency declines. Without this load shedding control, the greatest possible consequence is the blackout and the widespread outage.

For example, the FRCC load shedding program, has a load shedding plan under frequency load shedding shown in Table 5.

Table 5. The FRCC load shedding program

UFLS Steps	Frequency (Hz)	Time delay (s)	Amount of load (% of member system)	Cumulative amount of load (%)
A	59.7	0.28	9	9
B	59.4	0.28	7	16
C	59.1	0.28	7	23
D	58.8	0.28	6	29
E	58.5	0.28	5	34
F	58.2	0.28	7	41
L	59.4	10	5	46

In case of fault at generator 34 the load is 100%, when the system frequency drops to 59.7Hz, it was load shedding 9% of total load. System frequency continues to fall, and when dropped to 59.4Hz, load shedding 7% of total load. The system frequency started to stabilize, the total load shedding was 16% (9% + 7%).

B. Load shedding based on the AHP algorithm (Analytic Hierarchy Process) [11]

AHP is the approach to making decisions. This method presents balanced assessment options and criteria, and integrates them into a final decision. AHP is particularly suitable for cases involving analysis and quantification, make decisions when there are multiple options depending on the criteria with multiple interactions.

Strategic load shedding according to the AHP algorithm is shown in Table 6.

Table 6. The order of load shedding according to the AHP algorithm

Order	Load
1	L31
2	L12
3	L18
4	L26
5	L23
6	L25
7	L21
8	L28
9	L24
10	L3
11	L16
12	L15
13	L29
14	L27
15	L7
16	L20
17	L8
18	L4
19	L39

In the case of generator 34 outage, the load is 100%, load shedding according to AHP algorithm will be shed 31-12-18-26-23-25, the system is stability.

C. Simulate and compare methods with each other.

1. Frequency.

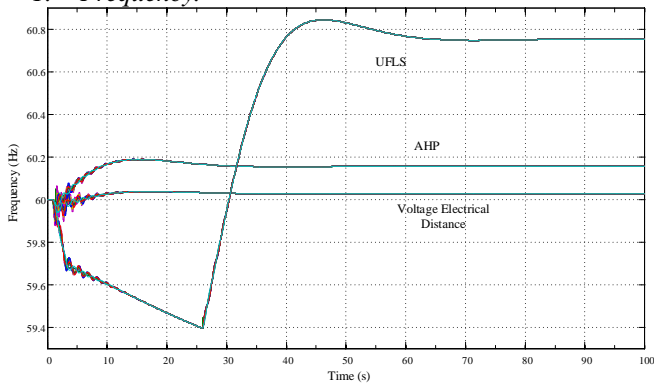


Fig. 14. Diagram of system frequency after generator 34 outage of all three methods of load shedding

Comparative results of the methods presented in Table 5.

Table 7. Comparative results of the methods

Method	Amount of load shedding (MW)	Frequency recovery time (s)	Frequency stability (Hz)
UFLS relay	975,52	65	60,75
AHP	785,2	47	60,157
Proposed	628	35	60,030

In the case of generators 34 outage with a load level of 100%, the proposed method has many advantages over the AHP method and the low frequency method, as follows:

The proposed load shedding method reduced the amount of load by 347.52 MW (55.3%) compared to the traditional load shedding method and 157.2 MW (25%) compared to the load shedding method based on the AHP algorithm.

The proposed load shedding method had a frequency recovery time of 30 seconds (85.7%) compared to traditional load shedding and 12 seconds faster (34.3%) than load shedding based on the AHP algorithm.

2. Voltage.

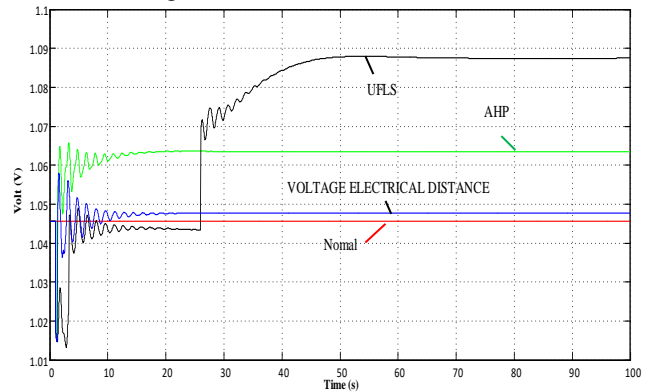


Fig. 14. Diagram of voltage after generator 34 outage of all three methods of load shedding

Table 8. Comparison of recovery voltages at 19 bus loads when 34 generators were lost for all three methods

Bus	Normal voltage (pu)	UFLS			AHP			Proposed		
		Recovery voltage (pu)	The change in voltage variation (%)	Recovery time (s)	Recovery voltage (pu)	The change in voltage variation (%)	Recovery time (s)	Recovery voltage (pu)	The change in voltage variation (%)	Recovery time (s)
Bus 3	1.054	1.094	3.74%	66	1.075	2.02%	52	1.056	0.14%	33
Bus 4	1.055	1.107	4.92%	85	1.082	2.58%	56	1.057	0.17%	33
Bus 7	1.056	1.109	5.07%	71	1.083	2.58%	54	1.057	0.15%	41
Bus 8	1.033	1.106	4.99%	71	1.079	2.49%	56	1.055	0.14%	47
Bus 12	1.045	1.105	5.71%	83	1.098	5.11%	53	1.047	0.19%	24
Bus 15	1.038	1.082	4.33%	72	1.059	2.05%	55	1.039	0.18%	29
Bus 16	1.046	1.084	3.68%	64	1.063	1.70%	38	1.048	0.18%	26
Bus 18	1.050	1.090	3.81%	85	1.074	2.27%	53	1.052	0.16%	34
Bus 20	0.993	0.990	0.27%	66	0.967	2.68%	27	0.998	0.47%	27
Bus 21	1.041	1.080	3.76%	67	1.059	1.73%	36	1.043	0.17%	32
Bus 23	1.049	1.090	3.93%	85	1.076	2.62%	34	1.051	0.20%	26
Bus 24	1.050	1.088	3.67%	69	1.068	1.76%	36	1.052	0.19%	34
Bus 25	1.065	1.098	3.16%	67	1.096	2.91%	43	1.066	0.12%	37
Bus 26	1.064	1.102	3.51%	67	1.091	2.48%	36	1.066	0.14%	27
Bus 27	1.052	1.092	3.76%	67	1.076	2.26%	31	1.054	0.15%	29
Bus 28	1.060	1.096	3.35%	70	1.081	1.97%	41	1.062	0.12%	26
Bus 29	1.058	1.092	3.18%	67	1.077	1.80%	35	1.059	0.12%	27
Bus 31	0.982	1.020	3.88%	70	1.002	2.00%	40	0.983	0.13%	29
Bus 39	1.030	1.038	0.73%	70	1.032	0.19%	44	1.030	0.02%	27
Average	1.04	1.08	3.65%	71.68	1.07	2.27%	43.16	1.05	0.17%	30.95

In the case of generators 34 outage with a load level of 100%, the proposed method has many advantages over the AHP method and the low frequency method, as follows:

The proposed load shedding method has a voltage recovery time of 131.6% compared to conventional method and 39.5% compared to the AHP algorithm.

The proposed load shedding method has better recovering voltage values than traditional methods and AHP algorithm methods as follows: the change in voltage variation compared to the voltage before the fault of proposed load shedding method is 0.17%, the traditional method is 3.65% and the AHP algorithm method is 2.27%.

VI. CONCLUSION.

The paper proposed a load shedding scheme with priority based on the voltage electrical distance between the fault node and the remaining nodes to ensure system stability in the event of a severe load imbalance in the event loss a generator occurring in the electric system. The effectiveness of the proposed load shedding program has been demonstrated by analyzing the simulation results of the IEEE 39 system, 10 generators. The results show that: the method of load shedding proposed to reduce the amount of load shedding, frequency recovery time, faster voltage, and better recovery voltage values than traditional methods and algorithm AHP.

ACKNOWLEDGMENT

This research was supported by Ho Chi Minh City University of Technology and Education, Ho Chi Minh City University of Technology and LacHong University DongNai province under a research.

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