

# Application of Dual Artificial Neural Networks for Emergency Load Shedding Control

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**Abstract**—This paper proposes a new model in emergency control of load shedding based on the combination of dual Artificial Neural Network to implement the load shedding, restore the power system frequency and prevent the power system blackout. The first Artificial Neural Network (ANN1) quickly recognizes the state with or without load shedding when a short-circuit occurs in the electrical system. The second Artificial Neural Network (ANN2) identifies and controls the selection of load shedding strategies. These load shedding strategies include pre-designed rules which is built on the AHP algorithm to calculate the importance factor of the load units and select the priority of the load shedding. In case the ANN1 results in a load shedding, the load shedding control strategy is immediately implemented. Therefore, the decision making time is much shorter than the under frequency load shedding method. The effectiveness of the proposed method is tested on the IEEE 39-bus system which proves the effectiveness of this method.

**Keywords**—Load shedding; Artificial Neural Network; AHP algorithm; emergency control; frequency stability

## I. INTRODUCTION

Short-circuit faults during operation are unpredictable and the time required for troubleshooting is also very short. If early system instability is detected and rapid shedding are implemented, it will prevent the system blackout and losing power completely. The conventional UFLS [1, 2] method is not suitable for the large and the complex power systems. For the most power companies, load shedding methods are implemented using a load balancing method, and it is not possible to shed the exact amount of load power because it is applied the entire feeder distribution line. UFLS relays are located at the first part of the feeder distribution line to control the breaker according to the frequency thresholds value. This value is set by the operator system regardless of the type of load, as well as the importance of the loads connected to the feeder. Therefore, the power supply will not be maintained to provide for the most important and necessary loads. Moreover, the coordination the frequency setting thresholds for UFLS relays for all feeder distributions line on a large power system nationwide is very complicated and difficult.

The recent large grid blackouts on the world [3-5] make the reliability of the UFLS, UVLS conventional techniques no longer as reliable as before in preventing power system blackout. The studies of intelligent load shedding [6, 7] focus

mainly on the objective of addressing the optimization of the load shedding power under the steady state operating mode of the power system. However, due to the complexity of the power system, in case of the emergency control, such as short circuits on branch and bus bars, these methods have problems with the amount of data, computation time and the processing speed of the algorithm program is relatively slow or the passive load shedding is done after waiting for the frequency below the permitted threshold, thus causing delays in the load shedding decision. This can lead to an instability of the power system frequency. In addition, these studies focused on the separate problem; it is the application of intelligent algorithms to solve the load shedding problem without combining with other problems, such as the problem of early warning recognition "Yes" or "No" of load shedding in a total solution to maintain power system frequency stability.

To overcome these problems, the dual neural network with the solution to identify "Yes" or "No" load shedding is applied. This solution has the ability to meet the classification requirements rapidly when short circuits occur incidents destabilize frequency in the power system. In case the load shedding recognition result of the ANN1 is "Yes", this identification result coordinate with the load shedding control that has been pre-design by the application of Analytic Hierarchy Process (AHP) algorithm. It helps to quickly make decisions to control load shedding based on ANN2 to restore and maintain the frequency stability of the power system.

## II. LITERATURE REVIEW

Research on the application of ANN network to shed the load in the power system has been used and developed by many researchers. In [8] proposes load shedding method base on ANN network for the multi-generator system and 39-bus New England systems [9, 10]. The ANN network training process includes three variables inputs: total generation power, total load demand, frequency attenuation and one variable output is the minimum amount of load shedding power. The results show that this method performs faster load shedding than UFLS methods [11, 12]. Kottick [13] uses two neural network models to solve the power failure situation of the generator. The first neural network identifies the lowest minimum frequency in the event of an outage generator. The second neural network identifies how many stage to perform of load shedding. However, this study has not considered

emergencies such as short circuit and load shedding has not considered the importance of load. In [14], ANN network is used to quickly identify the stability of multi-generator system. This study has not yet been considered in combination with load shedding solutions to stabilize the power system.

In addition, the ANFIS method base on the combination of neural networks and fuzzy logic to determine the amount of load shedding power presented in [15]. This method has been tested on IEEE 300-bus test systems. The test results show that the ANFIS method gives an accurate amount of load shedding power. However, the ANFIS method can only work with Sugeno type systems [16].

In most of the previous studies involving ANN, the variable output was the total amount of load shedding. This variable output is not an actual signal, because it does not determine the number of loads that must be shed in each step.

The intelligent load shedding algorithms are proposed as: in [17-19], the Particle Swarm Optimization (PSO) is a random optimization algorithm proposed by Kennedy and Eberhart in 1995 to support the load shedding strategic proposal ... These studies focus primarily on the objective of addressing the optimization of the load shedding power under the steady state operating mode of the power system. However, these methods have certain limitations in applying them in real-time applications. As a result, these methods are not fast enough for load shedding in emergencies such as short circuits. The actual load shedding system takes place in real time, and in this section, the quick response of the neural network can give the ability to optimize the identification and shedding of the load in an instant.

In fact, for a large system, the amount of load shedding power is greater or less than the optimal amount of load shedding power and does not affect too much of the system frequency, it is necessary to consider the location and time of load shedding so that system parameters recover quickly and stable restoration of the power system.

The proposed method in this paper has the advantage of solving the integrated problem, while many other methods solve single problems mainly about optimizing the amount of load shedding power. The proposed method combines the disturbance classification problem in the power system to decide whether or not to shed the load and the problem of determining the location of the load need to shed based on the load importance factor.

The effectiveness of the proposed load shedding method is verified on the 10-machine New-England Power System diagram. The results of the proposed method are compared with the under frequency load shedding method. Fast recognition process of "Yes" or "No" perform load shedding when a short-circuit incident occurs causes frequency instability in the power system in combination with the established load-control solution based on AHP algorithm. Which helped the control system to make decisions on fast load shedding to help the power system keep its frequency stability, the frequency of the recovery system to the allowed value and faster recovery frequency than traditional load shedding.

### III. METHODOLOGY

#### A. Arrange the Shedding Priority of the Load units based on the Importance Factor

The application of Analytic Hierarchy Process (AHP) algorithm [20] is proposed by T.L. Saaty with the idea of using expert knowledge to rank the objects in a system. This algorithm arranges the priority for load shedding of the load units through the following steps:

Step 1: Identify the Load Centre areas  $LC_i$  and the load units  $L_j$  in the power system diagram, this division of load centres is based on the criteria that the loads are close to each other or in the same load cluster.

Step 2: Set up a hierarchy model based on the Load Centre areas and load units identified in Step 1.

Step 3: Set up judgment matrix  $LC_i$  and  $L_j$  showing the importance factor of load centres and the importance factor among loads in the Load Centre together. The values of the components in the judgment matrix reflect the operational experience of the operating expert on the importance of the relationship between the pair of factors presented in equation (1), (2).

$$LC = \begin{bmatrix} W_{K1}/W_{K1} & W_{K1}/W_{K2} & \dots & W_{K1}/W_{Km} \\ W_{K2}/W_{K1} & W_{K2}/W_{K2} & \dots & W_{K2}/W_{Dm} \\ \cdot & \cdot & \cdot & \cdot \\ W_{Kn}/W_{K1} & W_{Kn}/W_{K2} & \dots & W_{Kn}/W_{Km} \end{bmatrix} \quad (1)$$

$$L_j = \begin{bmatrix} W_{D1}/W_{D1} & W_{D1}/W_{D2} & \dots & W_{D1}/W_{Dn} \\ W_{D2}/W_{D1} & W_{D2}/W_{D2} & \dots & W_{D2}/W_{Dn} \\ \cdot & \cdot & \cdot & \cdot \\ W_{Dn}/W_{D1} & W_{Dn}/W_{D2} & \dots & W_{Dn}/W_{Dn} \end{bmatrix} \quad (2)$$

Where:  $m$  is the number of the Load Centre;  $n$  is the number of loads in a Load Centre;  $W_{Di}/W_{Dj}$  describe the relative importance of the  $i_{th}$  load compared to the  $j_{th}$  load;  $W_{Ki}/W_{Kj}$  describe the relative importance of the  $i_{th}$  Load Centre compared to the  $j_{th}$  Load Centre. The value  $W_{Di}/W_{Dj}$ ;  $W_{Ki}/W_{Kj}$  can be obtained from the experience of experts or system operators through the use of the 9-scaling method.

If both loads A and B are equally important, then the scaling factor will be "1".

If load A is a bit more important than load B, then the scaling factor of A to B will be "2".

If load A is slightly more important than load B, then the scaling factor of A to B will be "3".

If load A is relatively more important than load B, then the scaling factor of A to B will be "4".

If load A is more important than load B, then the scaling factor of A to B will be "5".

If load A is relatively more important than load B, then the scaling factor of A to B will be "6".

If load A is much more important than load B, then the scaling factor of A to B will be “7”.

If load A is extremely relatively important compared to load B, then the scaling factor of A to B will be “8”.

If load A is extremely important compared to load B, then the scaling factor of A to B will be “9”.

Step 4: Calculate the importance factor of the Load Centre areas together and the importance factor of the load units in the same load area on the basis of set up a judgment matrix. According to AHP principles, the importance factor of the load can be calculated through the calculation of the maximal eigenvalue and the corresponding eigenvector of the judgment matrix. The calculation steps using the root method are as follows:

Multiply all elements of each row in the judgment matrix

$$M_i = \prod_j X_{ij}, \quad i=1, \dots, n; j = 1, \dots, n \quad (3)$$

Calculate the nth root of  $M_i$

$$W_i^* = \sqrt[n]{M_i}, \quad i=1, \dots, n \quad (4)$$

Once done, obtain the following vector:

$$W^* = [W_1^*, W_2^*, \dots, W_n^*]^T \quad (5)$$

Normalize the vector  $W^*$

$$W_i = \frac{W_i^*}{\sum_{j=1}^n W_j^*}, \quad i=1, \dots, n \quad (6)$$

the eigenvector of the judgment matrix A, that is:

$$W = [W_1, W_2, \dots, W_n]^T \quad (7)$$

Step 5: Calculate the importance factor of the load units for the whole system.

The importance factor of the load  $W_{ij}$  for the whole system can be calculated from the equation (8).

$$W_{ij} = W_{LCi} \times W_{Lj} \quad L_j \in LC_i \quad (8)$$

Where:  $L_j \in LC_i$  it mean the  $L_j$  load is located in the  $LC_i$  Load Centre.

Step 6: Arrange in descending order of importance of each load unit to implement the load shedding strategy according to priority.

### B. The Method of Emergency Load Shedding is based on the use of Dual Artificial Neural Networks

The principle model of the load shedding method based on the quick identification of the status "Yes" or "No" of the load shedding is presented in Fig. 1 and the detailed model shown in Fig. 2.

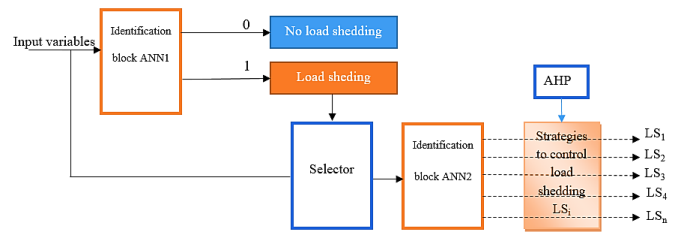


Fig. 1. Model of Emergency Control Principle for Load Shedding.

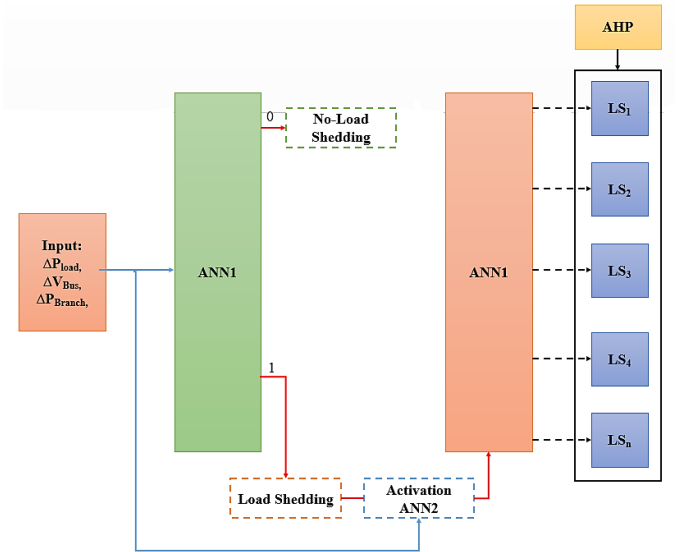


Fig. 2. Detailed Model of Emergency Load Shedding Control.

The principle of the load shedding method proposed is as follows: The input variable vector contains information specific to the state of the power system in the event of an incident and is collected from measuring devices. Parameters of the input variables contain an instant change of status parameters as soon as the problem occurs such as: amount of power change of the load bus ( $\Delta P_{load}$ ), voltage drop at buses ( $\Delta V_{bus}$ ), amount of power change on branches ( $\Delta P_{Branch}$ ). Based on these input variables, the first ANN1 neural network implement power system status identification "Yes" or "No" load shedding. If the output of ANN1 is "Yes" then the selector activates allowing the ANN2 to operate. ANN2 implements and identifies  $LS_i$  load shedding strategies ( $i = 1, n$ ) to control the load shedding strategy. These load shedding strategies are based on the AHP algorithm [20].

## IV. CASE STUDIES-SIMULATIONS AND RESULTS

The effectiveness of the proposed method is tested on the IEEE 39 bus 10 generators system. Rated frequency is 60Hz. This diagram is shown in Fig. 3.

PowerWorld software is used to off-line simulation to collect data for assessing the status of the electrical system with/without load shedding in the event of a short-circuit fault with 80%, 90% and 100% load levels of the base load, the short-circuit trip time of the circuit breaker is set to 50ms [22]. In these test, faults such as three-phase short-circuit, phase-phase, phase-to-earth at all bus bar and along the associated lines with each 5% distance of the line length are considered. The power system implements load shedding when the

frequency drops below the permitted level of 59.7Hz after the fault is cleared and vice versa. For ANN1, the input variable  $x$   $\{\Delta V_{bus}, \Delta P_{load}, \Delta P_{Branch}\}$  and the output variable  $y\{1, 0, 0, 1\}$ . The total number of input variables is 104 variables (including: 39 variables  $\Delta V_{bus}$ , 19 variables  $\Delta P_{load}$  and 46 variables  $\Delta P_{Branch}$ ), and 2 output variables (Including: load shedding, no load shedding). Synthesis of simulation cases for load levels built an input data set including 892 samples which includes 576 patterns that do not require load shedding and 316 samples need to be shed the load. During training of artificial neural network, the data set is divided into 85% data for training and 15% for test data. The data are normalized before training.

ANN1 is trained with neural network tools powered by Matlab software. Neural Perceptron configuration and parameters include 3 layers: input layer, hidden layer and output layer. The algorithm for updating weights and bias is Levenberg-Marquardt which is recommended for recognition problem due to its fast calculation and high accuracy [23]. Number of training cycles is 1000, training error is  $1e-5$ , other parameters are selected by default. The training results for ANN1 have a training accuracy of 98.81%, a test accuracy of 97.74% and the results are shown in Fig. 4.

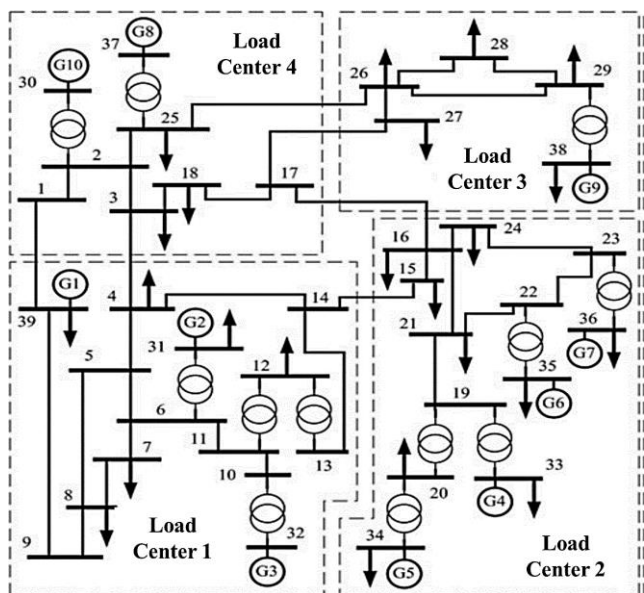


Fig. 3. Load Centre Areas in the IEEE 39 Bus 10 Generators System [21].

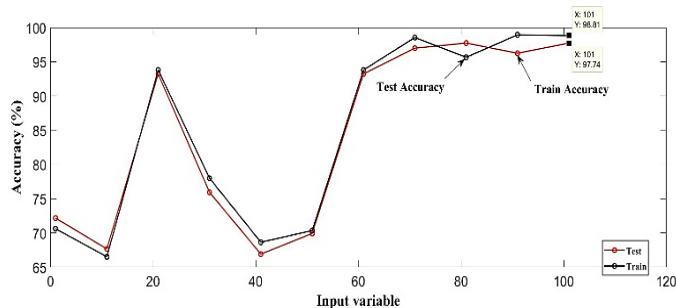


Fig. 4. Relationship of Training and Testing Accuracy Corresponds to the Number of Input Variables.

The steps of calculating importance weights are presented in Section II.A. Load Centre areas, load units in the IEEE 39 bus 10 generators and hierarchy model are shown in Table I and Fig. 5.

In the IEEE 39-bus 10 generators system, applying AHP algorithm to build 4 Load Centres, 19 load units are shown in Fig. 5. The judgment matrix of  $LC_i$  Load Centres and  $L_j$  loads in the Load Centre are presented from Tables II to Table VI.

TABLE I. LOAD CENTRE AREAS AND LOAD UNITS IN THE IEEE 39 BUS 10 GENERATOR DIAGRAM

Load centres	Load units
Load Centre 1 (LC1)	L <sub>4</sub> , L <sub>7</sub> , L <sub>8</sub> , L <sub>12</sub> , L <sub>31</sub> , L <sub>39</sub>
Load Centre 2 (LC2)	L <sub>15</sub> , L <sub>16</sub> , L <sub>20</sub> , L <sub>21</sub> , L <sub>23</sub> , L <sub>24</sub>
Load Centre 3 (LC3)	L <sub>26</sub> , L <sub>27</sub> , L <sub>28</sub> , L <sub>29</sub>
Load Centre 4 (LC4)	L <sub>3</sub> , L <sub>18</sub> , L <sub>25</sub>

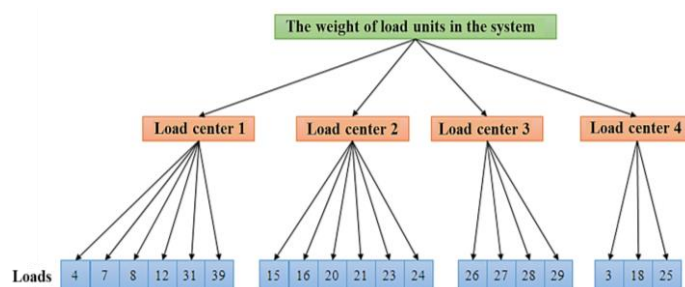


Fig. 5. Hierarchical Model of Load Centre and Load units.

TABLE II. THE JUDGMENT MATRIX OF LOAD CENTRE S

LC <sub>i</sub>	LC <sub>1</sub>	LC <sub>2</sub>	LC <sub>3</sub>	LC <sub>4</sub>
LC <sub>1</sub>	1/1	2/1	3/1	4/1
LC <sub>2</sub>	1/2	1/1	2/1	3/1
LC <sub>3</sub>	1/3	1/2	1/1	2/1
LC <sub>4</sub>	1/4	1/3	1/2	1/1

TABLE III. THE JUDGMENT MATRIX OF LOAD UNITS AT LOAD CENTRE 1

L <sub>j</sub>	L <sub>4</sub>	L <sub>7</sub>	L <sub>8</sub>	L <sub>12</sub>	L <sub>31</sub>	L <sub>39</sub>
L <sub>4</sub>	1/1	2/1	1/1	9/1	9/1	1/2
L <sub>7</sub>	1/2	1/1	1/2	8/1	8/1	1/5
L <sub>8</sub>	1/1	2/1	1/1	9/1	9/1	1/2
L <sub>12</sub>	1/9	1/8	1/9	1/1	1/1	1/9
L <sub>31</sub>	1/9	1/8	1/9	1/1	1/1	1/9
L <sub>39</sub>	2/1	5/1	2/1	9/1	9/1	1/1

TABLE IV. THE JUDGMENT MATRIX OF LOAD UNITS AT LOAD CENTRE 2

L <sub>j</sub>	L <sub>15</sub>	L <sub>16</sub>	L <sub>20</sub>	L <sub>21</sub>	L <sub>23</sub>	L <sub>24</sub>
L <sub>15</sub>	1/1	1/1	1/2	2/1	2/1	1/1
L <sub>16</sub>	1/1	1/1	1/2	2/1	2/1	1/1
L <sub>20</sub>	2/1	2/1	1/1	2/1	3/1	2/1
L <sub>21</sub>	1/2	1/2	1/2	1/1	1/1	1/1
L <sub>23</sub>	1/2	1/2	1/3	1/1	1/1	1/2
L <sub>24</sub>	1/1	1/1	1/2	1/1	2/1	1/1

TABLE V. THE JUDGMENT MATRIX OF LOAD UNITS AT LOAD CENTRE 3

$L_j$	$L_{26}$	$L_{27}$	$L_{28}$	$L_{29}$
$L_{26}$	1/1	1/2	1/2	1/2
$L_{27}$	2/1	1/1	2/1	1/1
$L_{28}$	2/1	1/2	1/1	1/2
$L_{29}$	2/1	1/1	2/1	1/1

TABLE VI. THE JUDGMENT MATRIX OF LOAD UNITS AT LOAD CENTRE 4

$L_j$	$L_3$	$L_{18}$	$L_{25}$
$L_3$	1/1	2/1	2/1
$L_{18}$	1/2	1/1	1/2
$L_{25}$	1/2	2/1	1/1

After building a judgment matrix, the AHP algorithm is applied to calculate the weight of the Load Centres and load units as follows:

Applying the equation (3), multiplying the values in the same row of each judgment matrix together calculates the  $M_{LCi}$  and  $M_{Lj}$  values. Then, apply Equation (4) to get the  $n$ th root of these  $M_{LCi}$  and  $M_{Lj}$  values, where  $n$  is the dimension of the judgment matrix, given the values  $W_{LCi}^*$  and  $W_{Lj}^*$ . Results of calculating values  $W_{LCi}^*$  and  $W_{Lj}^*$  are presented from Table VII to Table XI.

TABLE VII. THE  $M_{LCi}$  AND  $W_{LCi}^*$  VALUES OF LOAD CENTRES

$M_{LC1}$	24,00	$W_{LC1}^*$	2,21
$M_{LC2}$	3,00	$W_{LC2}^*$	1,32
$M_{LC3}$	0,33	$W_{LC3}^*$	0,76
$M_{LC4}$	0,04	$W_{LC4}^*$	0,45

TABLE VIII. THE  $M_{Lj}$  AND  $W_{Lj}^*$  VALUE OF LOAD UNITS AT LOAD CENTRE 1

$M_{L4}$	81,00	$W_{L4}^*$	2,08
$M_{L7}$	3,20	$W_{L7}^*$	1,21
$M_{L8}$	81,00	$W_{L8}^*$	2,08
$M_{L12}$	0,00	$W_{L12}^*$	0,24
$M_{L31}$	0,00	$W_{L31}^*$	0,24
$M_{L39}$	1620,00	$W_{L39}^*$	3,43

TABLE IX. THE  $M_{Lj}$  AND  $W_{Lj}^*$  VALUE OF LOAD UNITS AT LOAD CENTRE 2

$M_{L15}$	2,00	$W_{L15}^*$	1,12
$M_{L16}$	2,00	$W_{L16}^*$	1,12
$M_{L20}$	48,00	$W_{L20}^*$	1,91
$M_{L21}$	0,13	$W_{L21}^*$	0,71
$M_{L23}$	0,04	$W_{L23}^*$	0,59
$M_{L24}$	1,00	$W_{L24}^*$	1,00

TABLE X. THE  $M_{Lj}$  AND  $W_{Lj}^*$  VALUE OF LOAD UNITS AT LOAD CENTRE 3

$M_{L26}$	0,13	$W_{L26}^*$	0,59
$M_{L27}$	4,00	$W_{L27}^*$	1,41
$M_{L28}$	0,50	$W_{L28}^*$	0,84
$M_{L29}$	4,00	$W_{L29}^*$	1,41

TABLE XI. THE  $M_{Lj}$  AND  $W_{Lj}^*$  VALUE OF LOAD UNITS AT LOAD CENTRE 4

$M_{L3}$	4,00	$W_{L3}^*$	1,59
$M_{L18}$	0,25	$W_{L18}^*$	0,63
$M_{L25}$	1,00	$W_{L25}^*$	1,00

Normalize the matrix, applying equation (6) to find the weight values of the Load Centres  $W_{LCi}$  and the weight of the loads in each Load Centre  $W_{Lj}$ . The results of calculating these values are presented in Table XII to Table XVI.

TABLE XII. THE  $W_{LCi}$  VALUE OF LOAD CENTRES

$W_{LC1}$	0,47
$W_{LC2}$	0,28
$W_{LC3}$	0,16
$W_{LC4}$	0,10

TABLE XIII. THE  $W_{Lj}$  VALUE OF LOAD UNITS AT LOAD CENTRE 1

$W_{L4}$	0,22
$W_{L7}$	0,13
$W_{L8}$	0,22
$W_{L12}$	0,03
$W_{L31}$	0,03
$W_{L39}$	0,37

TABLE XIV. THE  $W_{Lj}$  VALUE OF LOAD UNITS AT LOAD CENTRE 2

$W_{L15}$	0,17
$W_{L16}$	0,17
$W_{L20}$	0,30
$W_{L21}$	0,11
$W_{L23}$	0,09
$W_{L24}$	0,16

TABLE XV. THE  $W_{Lj}$  VALUE OF LOAD UNITS AT LOAD CENTRE 3

$W_{L26}$	0,14
$W_{L27}$	0,33
$W_{L28}$	0,20
$W_{L29}$	0,33

TABLE XVI. THE  $W_{Lj}$  VALUE OF LOAD UNITS AT LOAD CENTRE 4

$W_{L3}$	0,49
$W_{L18}$	0,20
$W_{L25}$	0,31

After obtaining the values  $W_{LCi}$  and  $W_{Lj}$ , applying equation (8) calculates the values of the combined importance factor  $W_{ij}$  of each load. The  $W_{LCi}$  values at the same Load Centre are the same. The results of calculating the importance factors values of the load are presented in Table XVII.

The load units are arranged in ascending order the importance factor of the  $W_{ij}$ . In table XVIII, the load buses have the smaller weight which prioritized for shedding first in control strategies (Table XIX).

Based on the sorting order according to the increasing importance factor of the loads with respect to the system. The load has a small importance factor will be prioritized for shedding first and vice versa. Specifically, based on the results from Table XVIII, the  $L_{31}$  load will be prioritized for first shedding and the  $L_{39}$  load has the greatest importance factor for the final shedding. The load shedding is performed in accordance with the case of generator outage that need to be shed. The process of implementing this load shedding strategy is carried out until the frequency is within the permitted range of 59.7Hz. In fact, the importance of each load can vary from time to time in the 24-hour load chart. For example, the industrial zones loading area concentrates on production during office hours and off-peak hours, the living lighting area is heavily used in the evening. However, in order to simplify the calculation process, it is assumed that the order of load shedding above is unchanged by time and by consumption load level.

The results of load shedding strategies based on the AHP algorithm corresponding to the load simulation cases that must be performed for load shedding are presented in Table XIX.

TABLE XVII. IMPORTANT FACTOR OF THE LOAD CENTRES AND THE LOAD UNITS

Load	Load Centre	$W_{Lj}$	$W_{LCi}$	The combined importance factor $W_{ij}$
L <sub>4</sub>	LC <sub>1</sub>	0,224	0,467	0,10473
L <sub>7</sub>	LC <sub>1</sub>	0,131	0,467	0,06112
L <sub>8</sub>	LC <sub>1</sub>	0,224	0,467	0,10473
L <sub>12</sub>	LC <sub>1</sub>	0,025	0,467	0,01187
L <sub>31</sub>	LC <sub>1</sub>	0,025	0,467	0,01187
L <sub>39</sub>	LC <sub>1</sub>	0,370	0,467	0,17254
L <sub>15</sub>	LC <sub>2</sub>	0,174	0,278	0,04833
L <sub>16</sub>	LC <sub>2</sub>	0,174	0,278	0,04833
L <sub>20</sub>	LC <sub>2</sub>	0,296	0,278	0,08208
L <sub>21</sub>	LC <sub>2</sub>	0,110	0,278	0,03045
L <sub>23</sub>	LC <sub>2</sub>	0,091	0,278	0,02535
L <sub>24</sub>	LC <sub>2</sub>	0,155	0,278	0,04306
L <sub>26</sub>	LC <sub>3</sub>	0,140	0,160	0,02235
L <sub>27</sub>	LC <sub>3</sub>	0,330	0,160	0,05316
L <sub>28</sub>	LC <sub>3</sub>	0,200	0,160	0,03161
L <sub>29</sub>	LC <sub>3</sub>	0,330	0,160	0,05316
L <sub>3</sub>	LC <sub>4</sub>	0,493	0,100	0,04702
L <sub>18</sub>	LC <sub>4</sub>	0,196	0,100	0,01866
L <sub>25</sub>	LC <sub>4</sub>	0,311	0,100	0,02962

TABLE XVIII. ORDER OF LOAD SHEDDING ACCORDING TO AHP ALGORITHM

Oder of load shedding	Load	Load Centre	$W_{di}$	$W_{kj}$	The combined importance factor $W_{ij}$
1	L <sub>31</sub>	LC <sub>1</sub>	0,025	0,467	0,01187
2	L <sub>12</sub>	LC <sub>1</sub>	0,025	0,467	0,01187
3	L <sub>18</sub>	LC <sub>4</sub>	0,196	0,10	0,01866
4	L <sub>26</sub>	LC <sub>3</sub>	0,14	0,16	0,02235
5	L <sub>23</sub>	LC <sub>2</sub>	0,091	0,278	0,02535
6	L <sub>25</sub>	LC <sub>4</sub>	0,311	0,10	0,02962
7	L <sub>21</sub>	LC <sub>2</sub>	0,11	0,278	0,03045
8	L <sub>28</sub>	LC <sub>3</sub>	0,20	0,16	0,03161
9	L <sub>24</sub>	LC <sub>2</sub>	0,155	0,278	0,04306
10	L <sub>3</sub>	LC <sub>4</sub>	0,493	0,10	0,04702
11	L <sub>16</sub>	LC <sub>2</sub>	0,174	0,278	0,04833
12	L <sub>15</sub>	LC <sub>2</sub>	0,174	0,278	0,04833
13	L <sub>29</sub>	LC <sub>3</sub>	0,33	0,16	0,05316
14	L <sub>27</sub>	LC <sub>3</sub>	0,33	0,16	0,05316
15	L <sub>7</sub>	LC <sub>1</sub>	0,131	0,467	0,06112
16	L <sub>20</sub>	LC <sub>2</sub>	0,296	0,278	0,08208
17	L <sub>8</sub>	LC <sub>1</sub>	0,224	0,467	0,10473
18	L <sub>4</sub>	LC <sub>1</sub>	0,224	0,467	0,10473
19	L <sub>39</sub>	LC <sub>1</sub>	0,37	0,467	0,17254

TABLE XIX. LOAD SHEDDING STRATEGIES ARE BASED ON THE AHP ALGORITHM

Strategies to control load shedding	The loads are cut
LS <sub>1</sub>	L <sub>31</sub> , L <sub>12</sub>
LS <sub>2</sub>	L <sub>31</sub> , L <sub>12</sub> , L <sub>18</sub>
LS <sub>3</sub>	L <sub>31</sub> , L <sub>12</sub> , L <sub>18</sub> , L <sub>26</sub>
LS <sub>4</sub>	L <sub>31</sub> , L <sub>12</sub> , L <sub>18</sub> , L <sub>26</sub> , L <sub>23</sub>
LS <sub>5</sub>	L <sub>31</sub> , L <sub>12</sub> , L <sub>18</sub> , L <sub>26</sub> , L <sub>23</sub> , L <sub>25</sub>

ANN2 implements the recognition the load shedding strategies, the input variable similar to ANN1 includes 104 variables and the output variable includes five outputs corresponding to five load shedding control strategies based on the AHP algorithm. The process of developing strategies load shedding is shown above. Details of five load control strategies are presented in Table XIX. The input data of the ANN2 consists of 316 samples that need to be shed. During neural network training, the data set is divided into 85% data for training and 15% data for test. The data are normalized before training.

ANN2 is trained with the cases of using Back Propagation Neural Network (BPNN) with 4 training algorithms: Lenvenberg-Marquardt (trainlm), Bayesian (trainbr), Scaled Conjugate Gradient (trainscg), Resilient Backpropagation (trainrp) and use Generalized Regression Neural Networks (GRNN) to compare the effectiveness of training methods. Results of training accuracy and test accuracy of training methods are presented in Table XX and Fig. 6.

TABLE XX. TRAINING AND TEST ACCURACY OF ARTIFICIAL NEURAL NETWORK TRAINING METHODS

Training algorithm for ANN2	Levenberg-Marquardt (trainlm)	Bayesian (trainbr)	Scaled Conjugate Gradient (trainscg)	Resilient Backpropagation (trainrp)	Generalized Regression Neural Networks (GRNN)
Training accuracy (%)	66,29	92,88	39,13	42,32	98,50
Test accuracy (%)	56,52	71,74	36,96	41,57	95,65

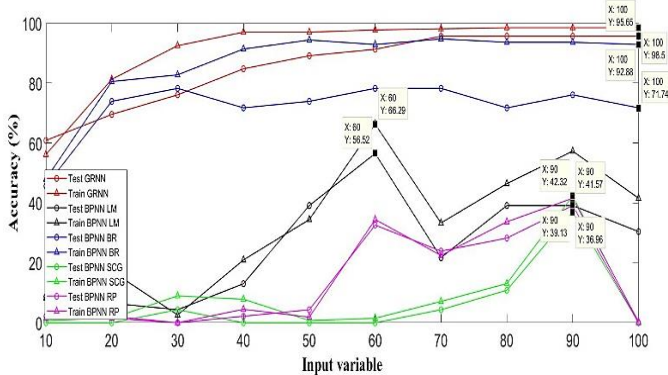


Fig. 6. Relationship of Training and Testing Accuracy Corresponding to the Input Variables of Artificial Neural Network Training Methods.

From the data results of Fig. 6 shows that in the case of recognition of load shedding strategy, GRNN training method has the highest accuracy. In addition, as the number of input variables increases, the accuracy also increases accordingly and reaches the highest precision value when it reaches 80 variables with a training accuracy of 98,5% and test accuracy of 95,7 %.

The proposed load shedding method is simulated to illustrate the diagram of the IEEE 39-bus 10 generators standard power system with the support of PowerWorld software for the disturbance at Bus 30.

In the study of power system stability, the time to load shedding  $t^{shed}$  is very important. This  $t^{shed}$  period greatly affects the stability of the system. The impact time of the under frequency load shedding relays (UFLS) is about 0.1s [24]. When applying intelligent computational algorithms, the proposed effective load shedding time is less than 500ms [22]. In this paper, the calculated load shedding time of 200ms includes: data acquisition measurement, data transfer, data processing and trip impact of the breaker. However, in order to ensure the safe amplitude in real time, as well as the permissible error, the 100ms interval is calculated [22]. Therefore, when simulating, the installation load cutting time is 300ms.

Specifically, considering the problem of a short circuit at Bus 32, the breakers will open the components: lines, generators connected to Bus 32 when short-circuited. A graph of the frequency of the system when disturbance at Bus 32 is shown in Fig. 7.

As observed in Fig. 7, when the load shedding is not implemented, the frequency of the system becomes unstable when the short-circuit fault occurs at Bus 32. Applying the proposed load shedding method, for short-circuit case at Bus 32, the result of recognition is that there is a load shedding and

LS<sub>5</sub> load shedding strategy is implemented. The time delay is about 300ms after the disturbance. The results of simulating the frequency of the power system when performing load shedding by the proposed load shedding method are presented in Fig. 8.

Comparing the proposed load shedding method with the traditional load shedding method using the under frequency load shedding (UFLS) relay [24] which is presented in Table XXI.

In this case, the delay time for load shedding is 2,88s after the disturbance, this time period includes: the time delay from the disturbance to the frequency below the permitted threshold of 59,7Hz is 2.6s, the time delay of relay UFLS, signal transmission and trip impact of breaker (0,28s). For this method, it is necessary to perform two steps of load shedding A and B because after the completion of step of load shedding A, the frequency has not been restored to the allowed value. The total amount of load shedding power for two steps A and B is 16% of the total power of the power system. The results of the simulation of the power system frequency during the load shedding by the traditional load shedding method UFLS are shown in Fig. 9.

In order to better understand the effectiveness of the proposed load shedding method, consider the case of a short-circuit failure at Bus 25. Performing the same steps as the case study when there is a short circuit at Bus 32. The result of recognition is that there is a load shedding and LS<sub>4</sub> load shedding strategy is implemented. The results of simulating the frequency of the power system are presented in Fig. 10 and Fig. 11.

The results of comparison between the proposed load shedding method and the traditional load shedding method [24] are presented in Table XXII.

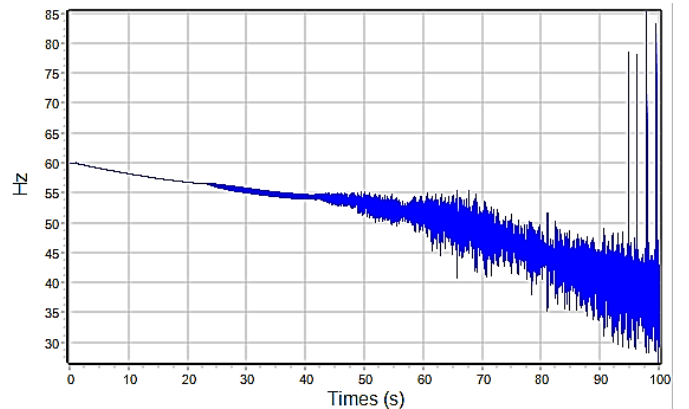


Fig. 7. The Frequency of the System when there is a Short Circuit at Bus 32.

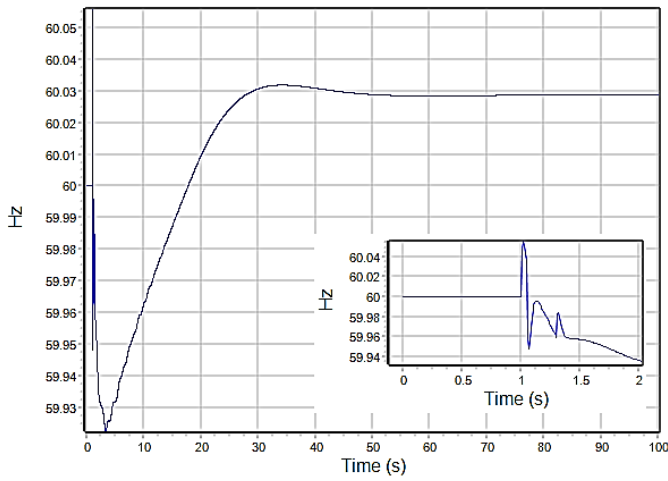


Fig. 8. The Frequency of the System when Load Shedding is Implemented by the Proposed Method.

TABLE XXI. THE UFLS SCHEME USING LOAD SHEDDING TABLE [11]

The steps UFLS	Frequency (Hz)	Time delay (s)	The amount of load shedding (the percent of total load) (%)	Total amount of load shedding (%)
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
M	59,7	12	5	51
N	59,1	8	5	56

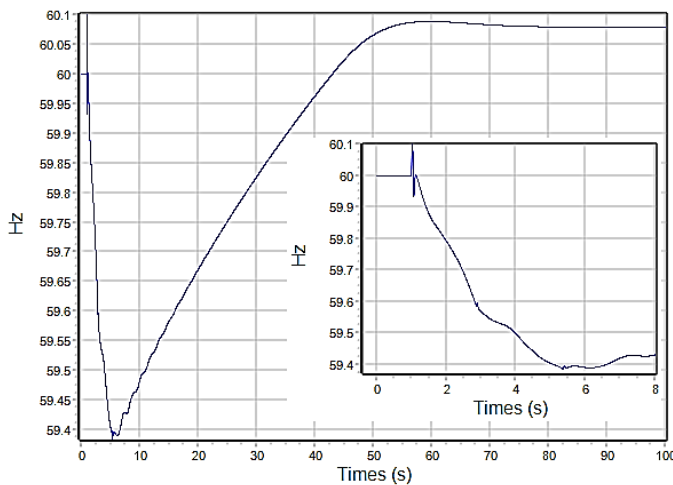


Fig. 9. The Frequency of the System when Load Shedding by the Traditional Method (UFLS).

Analysis of simulation results in Fig. 7, 8, 9, 10, 11 and Table XXII shows that the implementation of the proposed load shedding strategy helps the power system keep the frequency stability after the disturbance with recovery frequency value in the range 60,028Hz to 60.0455Hz.

Meanwhile, the traditional load shedding method (UFLS) has a greater amount of load shedding power from 2,28% to 24,2% and slower frequency recovery time from 10s to 28s.

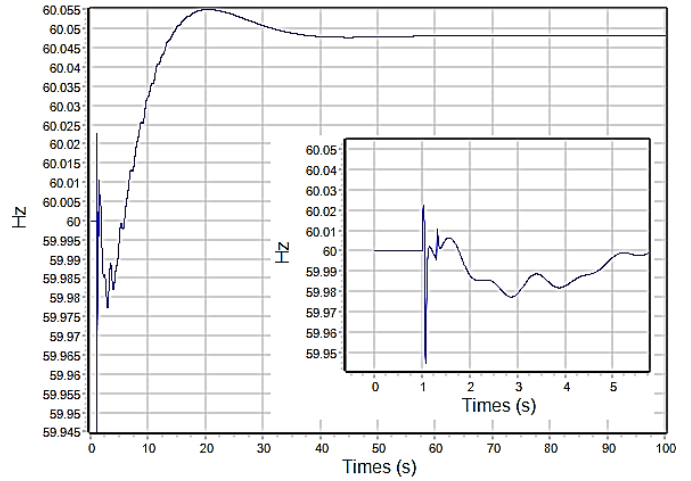


Fig. 10. The Frequency of the System when Load Shedding is Implemented by the Proposed Method in the Event of a Short Circuit Failure at Bus 25.

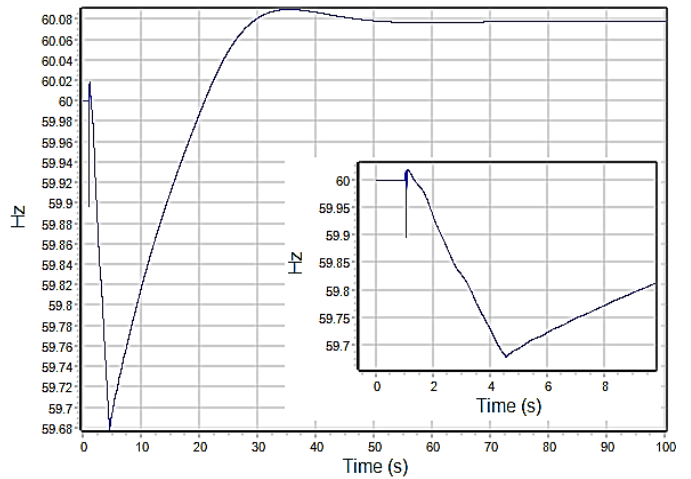


Fig. 11. The Frequency of the System when Load Shedding is Implemented by the Traditional Method (UFLS) in the Event of a Short Circuit Failure at Bus 25.

TABLE XXII. COMPARISON RESULT BETWEEN THE PROPOSED LOAD SHEDDING METHOD AND THE TRADITIONAL LOAD SHEDDING METHOD

	Frequency of recovery (Hz)	Time of recovery (s)	The amount of load shedding power (MW)
<b>Short circuit failure at Bus 32</b>			
The proposed load shedding method	60.028	50	628.2
The traditional load shedding method	60.055	78	780.4
<b>Short circuit failure at Bus 25</b>			
The proposed load shedding method	60.0455	40	438.9
The traditional load shedding method	60.0750	50	448.9



## V. CONCLUSION

The fast recognition process of "Yes" or "No" load shedding when a short-circuit incident occurs causes frequency instability in the power system in combination with the established load-control solution based on AHP algorithm supported the control system to make decisions on fast load shedding and keep the frequency stability of the power system. The frequency restored to the allowable value and the frequency of recovery time is faster than the traditional load shedding method.

Using the AHP algorithm to calculate and build a load shedding strategy group takes into account the importance factor of the load to reduce the economic loss when load shedding compared to previous traditional methods.

The effectiveness of the proposed load shedding method is verified on the IEEE 39 bus 10 generators power system diagram showing that the proposed load shedding method has helped maintain the system's frequency stability state. In the future work, the calculation of the load importance factor will apply Fuzzy-AHP algorithm to assist the experts more easily in making decisions to establish judgment matrices. The neural network training data set need to consider dynamic load and the load operates at different levels. Besides, the load shedding problem will take into account the optimal amount of load shedding and solve the economic and technical multi-objective problems using intelligent algorithms such as GA, PSO.

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