# The Application of Neural Networks for Supervising the Instability of Frequency in Microgrid Systems

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ABSTRACT

This article presents a method for identifying conditions of load shedding in Microgrid power systems based on the use of an Artificial Neural Network (ANN). The sample set to train the ANN is built using simulation software with different failure scenarios. The sample set is a matrix containing information about variables and samples. Input variables selection for the ANN is accomplished using the Binary Particle Swarm Optimization (BPSO) algorithm. The BPSO algorithm is applied to reduce the input space by evaluating the results by the K-nearest neighbor identifier (K-NN, K=1). The sample set after being processed to reduce variables is the sample set to train ANN to identify load shedding conditions. The rapid identification of load shedding conditions in the electrical grid facilitates swift decision-making for implementing load shedding and enhances the stability of the power system. In this work, a load shedding method based on the Analytic Hierarchy Process (AHP) prioritization of loads is also applied. The effectiveness of the proposed method is applied for a IEEE 25-bus Microgrid system. Research results indicate high accuracy in identification, making the proposed load shedding control method more efficient than other approaches.

## 1. INTRODUCTION

Evaluating stability status of an electrical power system (ES) is a complex problem that requires multiple practical solutions. Rapid assessment of the stability status of a power system enables quick decision-making for control actions to maintain system stability. Particularly in Microgrid, the presence of non-dispatchable sources exacerbates the system's susceptibility to instability under disturbances. These grids often integrate numerous renewable energy sources, making them a promising solution for more efficient, reliable, and environmentally friendly energy infrastructure. The article [1] introduced research results on policies and challenges in Microgrid development. In [2] presented the method for building photovoltaic (PV) parameter estimation models. However, ensuring continuous and reliable power supply in Microgrid, especially under islanded operation conditions, remains a significant challenge.

The study [3] discusses the utilization of the Fast Van turbine to expedite the restoration of power system stability and prevent grid desynchronization. Rapid state identification is achieved through on-site measuring devices and the application of a method predicting power angle characteristics to anticipate instability and calculate the amplitude of stable states.

One of the crucial issues in Microgrid management is the identification of events with or without load shedding. Load shedding is the intentional reduction of electricity demand to prevent power supply interruptions, and it is a necessary strategy when a Microgrid faces energy imbalance or equipment failures. Early detection of these events is essential for maintaining uninterrupted power supply, improving system efficiency, and minimizing disruptions for end-users [4].

For traditional methods, the identification of load shedding relies on algorithms and complex models that consider a range of variables, including the states of network components and operational parameters. In a standard Microgrid network, there can be numerous different variables to monitor, making real-time identification of load shedding a highly complex and resource-intensive task.

Previous studies on load shedding are presented in [5]-[11]. These studies primarily focus on addressing load shedding issues when it is already certain that a load shedding event will occur. However, in Microgrids, there are various incidents and disturbances, and not every incident necessarily requires load shedding.

There are several studies about fault identification in power systems. For instance, in [12], the STGCN-DDQN technique (Spatio-Temporal Graph Convolutional Network

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- Double Deep Q-Network) is presented. In [13], a combination of simple traditional algorithms like Singular Value Decomposition and K-means is discussed, along with a novel concept built on the gradient of clustered data. In [14], a method for determining the temporary stable boundaries in a multidimensional uncertain power system is introduced. This approach uses parameter space rather than state space to determine operational states. These methods have many new points in terms of recognition methods, however streamlining data through reducing the size of input variables to speed up processing needs to be considered. This is a crucial issue in the field of system identification.

Many studies focus on data preprocessing for identification, aiming to eliminate redundant variables and improve processing time. In [15], the GP-IDENT algorithm is proposed, utilizing a B-spline basis to represent coefficients varying in both unknown space and time, pursuing the expected subspace of the group (GPSP) to find candidate PDE sequences with differing levels of complication, introducing a new measure for model selection apllying Residual Reduction (RR) to select an optimize criterion with candidate groups. In [16], an automated variable selection procedure is presented for classification tasks and regression, providing the finest stability index without needing any previous information about the samples. In [17], an improved method is proposed for Arabic text classification using Chi-square feature selection to enhance classification performance.

In this study, we offer an innovative approach for identifying whether or not there is load shedding events in a Microgrid network, utilizing an ANN and the BPSO algorithm [18] to reduce the input variable space for this problem. The approach is planned to curtail the number of input for the identificationer, aiming to calculate and identify load shedding quickly without affecting accuracy.

The combination of BPSO algorithm to reduce variables and apply ANN network helps identify load shedding more effectively and improve real-time decision-making ability for operational management, thereby maintaining the stability of the Microgrid.

## 2. MATERIALS AND METHODS

### *2.1. Frequency stability in power systems*

Frequency stability [19] is the capability of a ES to regulate and keep a stable, especially after harsh turbulences [20] that may piplot to instability frequency [21]. The stability depends on the ES's ability to recover to a well-adjusted state. This issue is associated with various factors such as the control of power generator units, protective devices, and the response of control equipment.

Load control also plays a significant role in frequency control by utilizing the self-adjusting effect of frequency-sensitive loads. However, this object is not always considered in the overall frequency control response calculations. Load control can help reduce $CO_2$ emissions and operational costs in the power system.

Finally, when system adjustment measures are no longer effective, load shedding becomes a necessary consideration. According to the IEEE standard "IEEE Guide for the Application of Protective Relays Used for Abnormal Frequency Load Shedding and Restoration", “C37.106 TM, IEEE Guide for Abnormal Frequency Protection for Power Generating Plants”, the allowable frequency attenuation is 0.3Hz. This is a crucial reference value when deciding whether or not to implement load shedding during the process of constructing training datasets for neural networks.

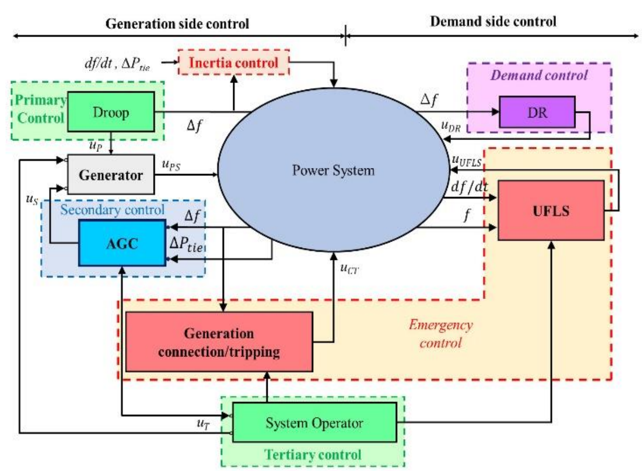


**Fig. 1. The process of frequency control in power system.**

In the Fig. 1 [22], we observe that frequency control depends on various factors such as the change in tie line power $\Delta P_{tie}$, the power change of generators after control processes based on frequency deviation ΔPG, and the load fluctuation $\Delta P_d$. Additionally, factors related to voltage and frequency variations over time during the dynamics also need to be considered. These are parameters that represent the system state when a problem occurs. These parameters are suitable to be selected as identification data related to frequency and conditions for making control decisions.

### *2.2. Neural network model*

The mathematical model of a neural network was introduced by McCulloch and Pitts in 1943 [23]. In the ANN model, the processing element at the *j-th* node calculates the weighted sum of its inputs, and the output $Y_j$ is either 1 or 0 depending on whether this weighted sum is below or above the threshold value ($\theta_j$). Fig. 2 is a model of feedforward neural network.

$$Y_j(t+1) = f(\sum_{i=1}^{I}(W_{ij}X_j(t) - \theta_i)) \tag{1}$$

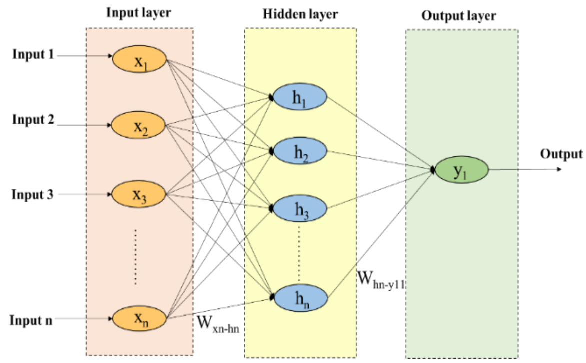


**Fig. 2. Model of feedforward neural network.**

The weight, $W_{ij}$, illustrates the intensity of the synaptic bond from neural $i^{th}$ to neural target $j^{th}$. A positive $W_{ij}$ corresponds to an excitatory synapse, while a negative $W_{ij}$ corresponds to an inhibitory synapse. If $W_{ij}$ equal zero then there is not tie between them.

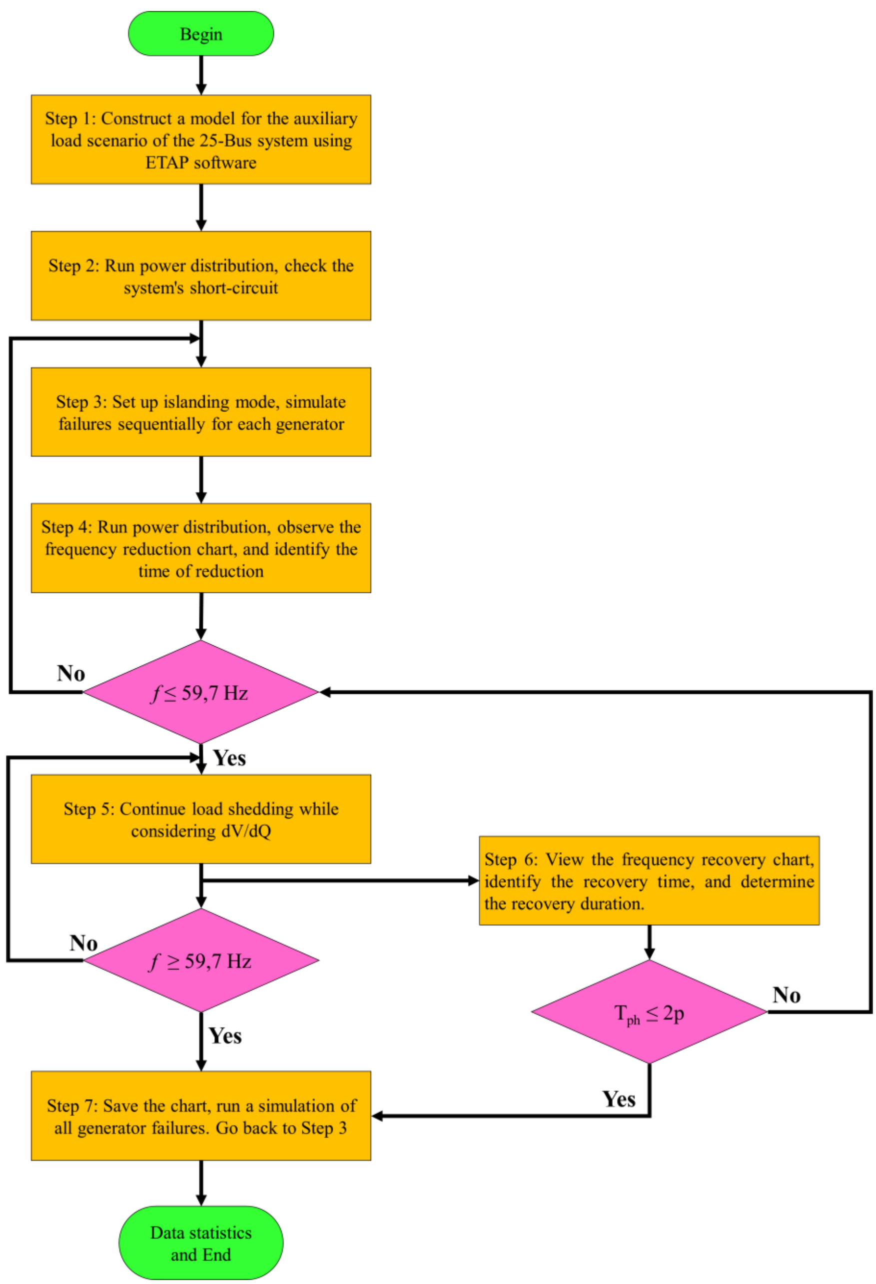


**Fig. 3. The flowchart of data collection process.**

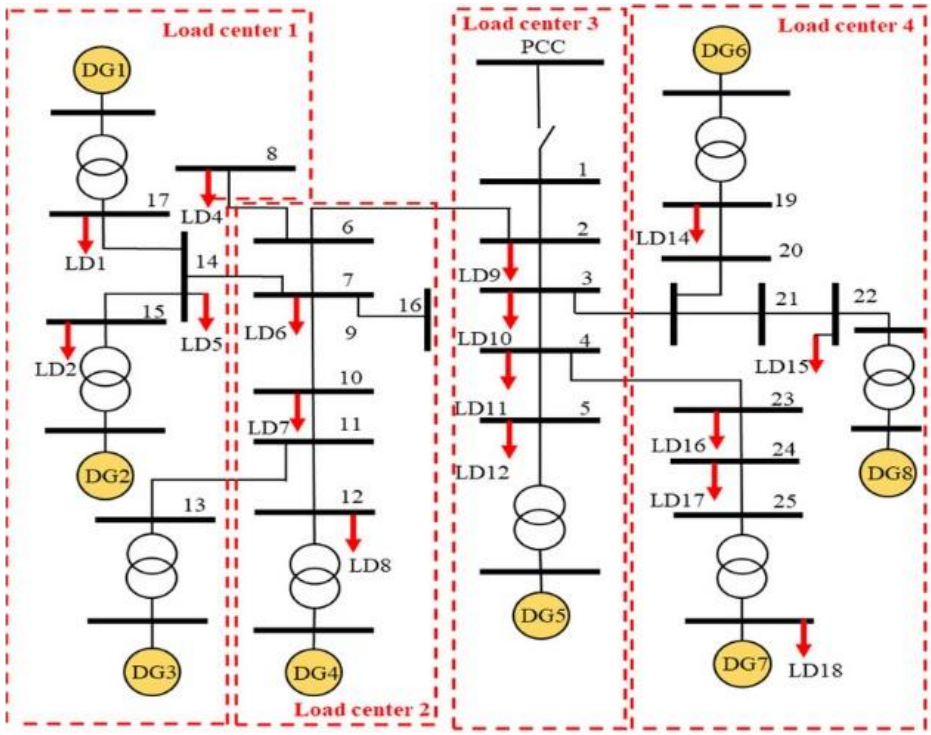


**Fig. 4. IEEE 25 bus Microgrid diagram.**

### *2.3. Build the data set*

The data is constructed in an offline simulation mode to assess the state of the ES with or without load shedding during frequency disturbances at various load levels. Fig.3 depicts the data collection process. Specifically, starting from a electrical power system diagram, power distribution is conducted, and the system is tested for generator tripping incidents where the generators disconnect from the power system. Subsequently, an iterative process is initiated, transitioning the system into islanded mode at each iteration is achieved by disconnecting the source grid simultaneously altering the generator positions to create generator tripping incidents. Throughout the incident creation process, observing and recording the fluctuating values of parameters in the power system, each iteration yields a sample for the training dataset. The data collection process is carried out at various load levels.

For incidents created, a thorough examination and classification of the data are performed. In cases where the frequency value decreases below the permissible threshold, the output variable is set to {1}, indicating load shedding. The shedding strategy is then executed, and the effectiveness of the shedding strategy is evaluated. On the other hand, if the frequency value is within the allowed range, the output variable is set to {0}, and the process proceeds to the next step until the loop termination condition is met. The ANN training data includes input variables x$\{\Delta U_{bus}, \Delta P_d, \Delta P_{tie}, \Delta P_G, \Delta f_{bus}\}$ and output variables y{1,0}.

### *2.4. The proposed load shedding prediction model*

The IEEE 25 Bus model is commonly used in research related to power system stability, load imbalance, and other issues associated with the performance and safety of electrical systems. It serves as a foundation for testing and evaluating algorithms and simulation methods in the literature [24, 25]. In the simulation, parameters related to transmission lines, loads, and generators, such as excitations and governors, were referenced from [26, 27].

Fig. 5 depicts the process of constructing the load shedding condition recognition model. Starting from the standard power grid, after simulating assumed generator outages, data is collected, including critical system parameters such as Bus Voltage, Bus Frequency, Transmission Power, Generator Power, and Load Power. The dataset comprises m initial variables, with s samples corresponding to each fault scenario with load levels ranging from 50-100%. The process of collecting system parameters to build the data set is described in "Section 2.3". The BPSO algorithm is applied to select representative variables from the dataset, with m variables (m<M). The dataset for training the ANN-based recognition model is constructed with a size of (m×s).

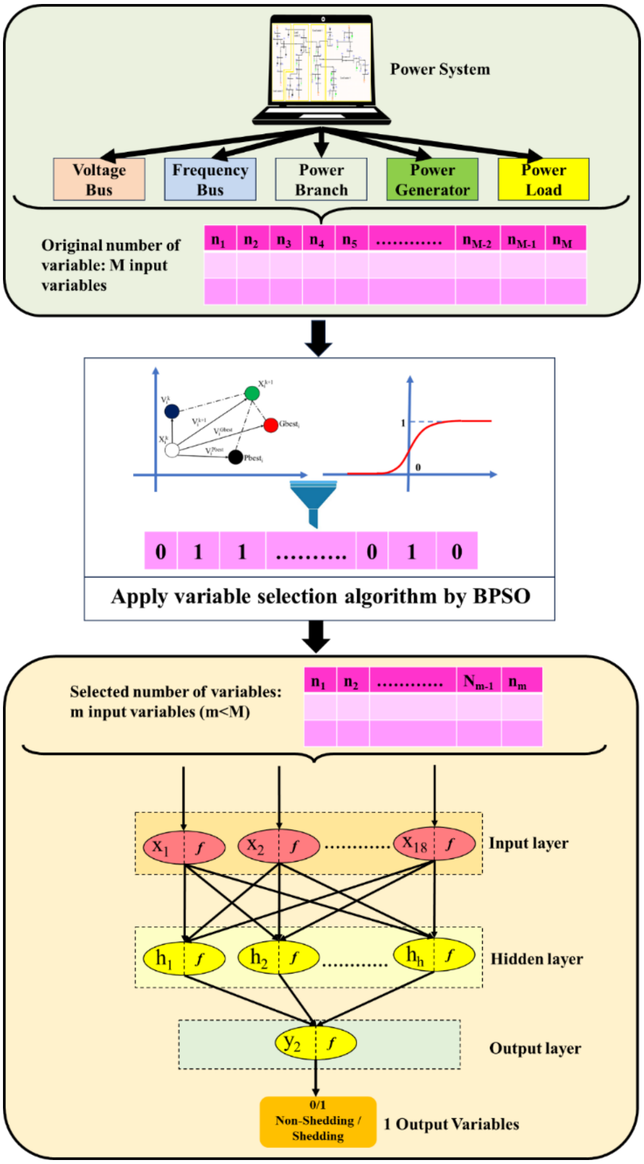


**Fig. 5. Constructing Load Shedding Condition Recognition Model.**

## 3. RESULTS

The BPSO algorithm is executed with various values of N. In this study, N takes on the following values respectively: N = [10, 20, 30, 40, 50, and 100], w = 0.9, T = 100, c1 = 2, c2 = 2. The selected evaluation feature-set is K-NN (K-nearest neighbor). The classification error 1-NN is assessed using the cross-validation method with k-folds = 10. The objective function for the 1-NN recognizer to evaluate and select variables is presented according to formula (2), the recognition error applies formula (3).

$$\mathit{Fitness} = \frac{\mathit{classification\ error}}{\mathit{Initial\ variables\ number} - \mathit{Selected\ varibales\ number}} \quad (2)$$

$$\mathit{Classification\ Error} = \frac{\mathit{samples\ error\ number}}{\mathit{total\ number\ of\ samples}} \quad (3)$$

The computational functions are supported by MATLAB 2021a software. The calculated results are shown in Table 1. Fig. 6 shows the convergence curves of the algorithm.

**Table 1. Variable selection algorithm execution results**

| N | SV | Best (Fitness) | CE (%) |
|---|---|---|---|
| 10 | 29 | 2.3e-05 | 0.65 |
| 20 | 27 | 2.26e-05 | 0.22 |
| 30 | 25 | 2.22 e-05 | 0.44 |
| 40 | 22 | 2.15 e-05 | 0.87 |
| 50 | 22 | 2.15 e-05 | 0.87 |
| 100 | 18 | 2.07 e-05 | 0.87 |

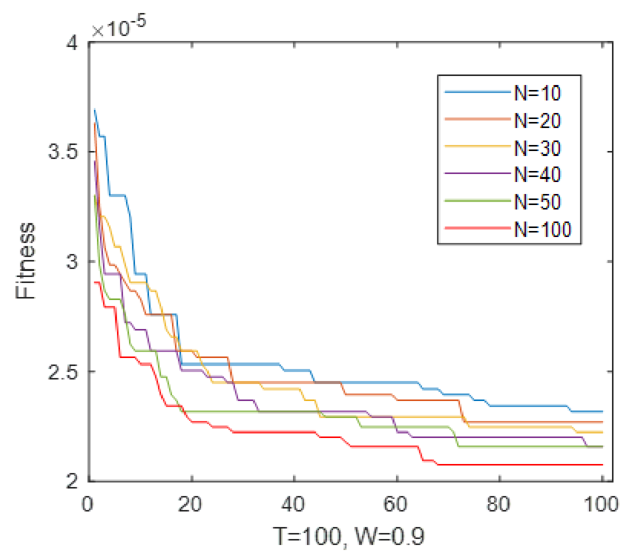


**Fig. 6. Convergence characteristic of the BPSO variable selection algorithm execution.**

From the results in Table 1, 18 input variables were selected. This is the input for constructing the ANN model that recognizes the output for load shedding conditions. Therefore, the constructed neural network model has 18 input variables and 1 output, indicating the status of the power grid whether load shedding is implemented or not. A '0' output implies no load shedding control, while a '1' output commands load shedding. In this paper, it is recommended to apply feedforward neural networks to build a supervised neural network model for load shedding conditions. The ANN tools are supported by MATLAB software. The neural network function applied is feedforwardnet. The network is constructed with the training functions `trainscg`, `trainrp`, `trainbfg`, and `trainlm` respectively. The number of hidden neurons chosen for all training runs is 10. The number of initial input is 123 (36 for $\Delta U_{bus}$, 18 for $\Delta P_d$, 25 for $\Delta P_{tie}$, 8 for $\Delta P_G$, 36 for $\Delta f_{bus}$), and one output variable. The dataset comprises 459 samples. It is randomly partitioned into a training and a testing subset. The training subset contains 367 samples, with 127 samples labeled '1' and 240 samples labeled '0'. The testing subset consists of 92 samples, including 40 samples of class '1' and 52 samples of class '0'. The results for 5 training functions are depicted in Figure 7, and the average results for the 5 iterations are summarized in Table 2.

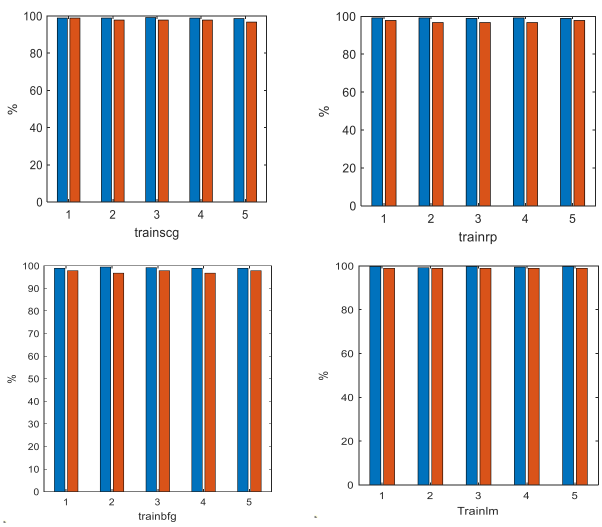


**Fig. 7. Results of 5 training iterations.**

**Table 2. The average result of 5 training functions**

| Training Algorithm | Training (%) | Testing (%) |
|---|---|---|
| trainscg | 98.91 | 97.82 |
| trainrp | 99.07 | 97.17 |
| trainbfg | 99.07 | 97.39 |
| trainlm | 99.56 | 98.9 |

The load shedding prediction model utilizes a neural network with processed data to reduce variables and make decisions between Shedding/Non-shedding. In the case of load shedding prediction, the model will make decisions to execute load shedding strategy by applying the load shedding based on the AHP method. In this method, important weights are used to rank loads during the shedding process. The AHP [28] is applied to determine the importance weights of loads and consult experts. The process of implementing the AHP algorithm is described in [29]. Load regions and clusters are depicted in Fig. 4. The judgment matrix (JM) of load clusters (LC) and loads within the load (Ld) clusters is presented in Table 3 and Table 4. The ranking of loads are shown in Table 5.

**Table 3. The JM of LC**

| LC | LC1 | LC2 | LC3 | LC4 |
|---|---|---|---|---|
| LC1 | 1 | 1 | 1/3 | 1/5 |
| LC2 | 1 | 1 | 1/2 | 1/3 |
| LC3 | 3 | 2 | 1 | 1/3 |
| LC4 | 5 | 3 | 3 | 1 |

**Table 4. The JM of loads within the LC**

| **Ld** | **Ld1** | **Ld2** | **L4** | **L5** |
|---|---|---|---|---|
| Ld1 | 1 | 1 | 1/3 | 1/2 |
| Ld2 | 1 | 1 | 1/3 | 1/2 |
| Ld4 | 3 | 3 | 1 | 2 |
| Ld5 | 2 | 2 | 1/2 | 1 |
| **Ld** | **Ld6** | **Ld7** | **Ld8** | |
| Ld6 | 1 | 1/3 | 1/3 | |
| Ld7 | 3 | 1 | 1/2 | |
| Ld8 | 3 | 2 | 1 | |
| **Ld** | **Ld9** | **Ld10** | **Ld11** | **Ld12** |
| Ld9 | 1 | 2 | 2 | 1/2 |
| Ld10 | 1/2 | 1 | 2 | 1/3 |
| Ld11 | 1/2 | 1/2 | 1 | 1/2 |
| Ld12 | 2 | 3 | 2 | 1 |
| **Ld** | **Ld14** | **Ld15** | **Ld16** | **Ld17** |
| Ld14 | 1 | 2 | 2 | 3 |
| Ld15 | 1/2 | 1 | 2 | 3 |
| Ld16 | 1/2 | 1/2 | 1 | 2 |
| Ld17 | 1/3 | 1/3 | 1/2 | 1 |

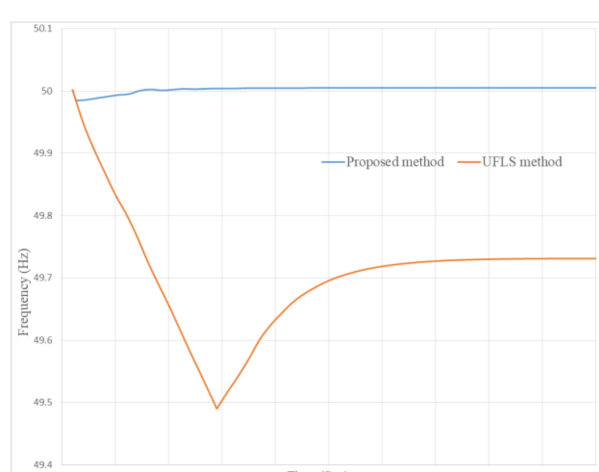


**Fig 8. The recovery frequency values of 2 load shedding methods.**

Load shedding is implemented in order of decreasing importance, where loads with smaller coefficients are shed first. This strategy continues until the system frequency reaches 49.5Hz. The loads that need to be shed in this case include the order of loads: Ld1, Ld2, Ld6, Ld5, Ld11, Ld10, Ld7. The total shedding power is 141.25 kW. The shedding action is executed with a duration of 500ms, starting from the moment when the load shedding identification result is confirmed [30].

The results of comparing the recovery frequency in the case of load shedding according to the suggested method and the Under frequency load shedding (UFLS) method are presented in Fig. 8. The study case is when the ES operates at 90% of the base load, in the islanded mode.

The results indicate that with the same volume of load shedding, the proposed method shows a better frequency recovery quality at 50Hz compared to the UFLS method at 49.73Hz.

**Table 5. Load shedding order according to the AHP**

| Ld | LC | $W_{Loadj}$ | $W_{LCi}$ | $Wcoe_{ij}$ (The aggregate importance coefficient) |
|---|---|---|---|---|
| Ld 1 | LC1 | 0.1411 | 0.1031 | 0.0146 |
| Ld 2 | LC1 | 0.1411 | 0.1031 | 0.01456 |
| Ld 6 | LC2 | 0.1396 | 0.1297 | 0.0181 |
| Ld 5 | LC1 | 0.2627 | 0.1031 | 0.0271 |
| Ld 11 | LC3 | 0.1350 | 0.2414 | 0.0326 |
| Ld 10 | LC3 | 0.1725 | 0.2414 | 0.0416 |
| Ld 7 | LC2 | 0.3325 | 0.1297 | 0.0431 |
| Ld 4 | LC1 | 0.4550 | 0.1031 | 0.0469 |
| Ld 17 | LC4 | 0.1078 | 0.5258 | 0.0567 |
| Ld 9 | LC3 | 0.2610 | 0.2414 | 0.0652 |
| Ld 8 | LC2 | 0.5278 | 0.1297 | 0.0685 |
| Ld 16 | LC4 | 0.1867 | 0.5258 | 0.0982 |
| Ld 12 | LC3 | 0.4225 | 0.2414 | 0.1020 |
| Ld15 | LC4 | 0.2922 | 0.5258 | 0.1536 |
| Ld14 | LC4 | 0.4133 | 0.5258 | 0.2173 |

## 4. DISCUSSION

In terms of dimensionality reduction, applying the BPSO algorithm with a 1-NN evaluation set, the initial set of 123 variables is reduced to 18 variables, achieving a reduction to 85.36% of the original input size. Meanwhile, the training and testing recognition accuracy with the trainlm algorithm achieved high results of 99.56% and 98.9%, respectively, the remaining training algorithms all achieved testing accuracy of over 97%.

The proposed method, due to the Shedding/No Shedding identifier, has a much earlier shedding time of 500ms compared to the traditional method (14.5s). It has to delay for the frequency to drop below the limit of 49.5Hz. This time period is relatively long compared to quickly identifying Shedding/No Shedding right from the time of the incident. That helps the proposed shedding method to have earlier impacts on the system, such as load shedding actions that help the system quickly recover with a faster time (10s) compared to the UFLS method (35s), the recovered frequency quality is better (50Hz) than the UFLS method (49.73Hz).

The problem of evaluating power system frequency stability deals with emergency situations. Therefore, it requires very quick handling of technical aspects to maintain system frequency stability electrical system. The technical priority is greater than the economic one. Therefore, we have not considered optimal load shedding. Normally, the problem is considered under condition of operating the ES at steady state. There, economic problems are given more priority. Furthermore, we have ranked loads in order of priority for load shedding. it can still help reduce the damage caused by load shedding.

## 5. CONCLUSION

The test results demonstrate that reducing the input dimensionality for the load shedding condition recognition system maintains a high level of accuracy. This is of great significance in reducing the cost of purchasing measurement sensor devices, reducing the input variables for the recognition system. As a result, it helps minimize memory storage requirements and accelerates computational speed in constructing the model.

The rapid identification of Shedding/No Shedding significantly enhances the frequency recovery quality by approximately 0.27Hz and the recovery time is 25 seconds faster than the UFLS method. This demonstrates the superiority and value of the proposed method. It could potentially apply self-learning and self-training tools to enhance its "intelligence and adaptability" in constructing training samples, thereby improving the accuracy of the proposed method.

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