PREVENTIVE CONTROL OF ELECTRICAL POWER SYSTEMS BASED ON DYNAMIC SECURITY PREDICTION

Ha Van Du[(1)], Nguyen Ba Thanh[(1)]

(1) Thu Dau Mot University

Corresponding author: duhv@tdmu.edu.vn

DOI: 10.37550/tdmu.EJS/2024.02.557

Article Info

Volume: 6
Issue: 02
June 2024
Received: Feb 29th, 2024
Accepted: May 11th, 2024
Page No: 288-296

Abstract

The power system is increasingly expanding, especially with the increasing participation of distributed renewable energy power plants, increasing the level of instability when operating the power grid. This study proposes a solution to help improve the stability of the power system through preventive control based on dynamic security prediction results. The proposed method is implemented using Matlab software with a network model of 10 buses, 4 generators, and simulated input data according to IEEE standards. The data from the simulation results is fed into the fuzzy logic system to determine the optimal grid operation plan. The results of this research help power grid operators come up with reasonable operating mechanisms to improve their ability to operate the power grid safely and stably.

Keywords: dynamic security, fuzzy logic, neural network, power systems

1. Introduction

The transmission of large capacity leads to the operating conditions of the transmission lines near to the working limit. As a result, power system (PS) become susceptible to turbulence and power outages that cause heavy damage (Andersson et al., 2005; Makarov et al., 2005). The urgency has become apparent when in recent years, power outages have severely affected the economy in many countries around the world (Furse et al., 2021). In recent years, due to the ability to quickly learn the input and output nonlinear relationships of the power system operating conditions, artificial neural networks (ANN) are an approach to evaluate the stability of the power system that has attracted many researchers' attention (Bento, 2024; Maraaba et al., 2023; Wazirali et al., 2023). Based on the steady state variables of the power system, it is possible to diagnose the operating state of the power system when a fault occurs. Then, preventive control will help protect the electrical system against unexpected factors that can cause power outages. The study was carried out on the power system of 4 generator – 10 buses (Uravakonda et al., 2022) with support for simulation and calculation software Matlab R2014a.

2. Research Methods

2.1. Artificial Neural Network

ANN learns the input and output data relationships to evaluate the power system state. The characteristic variables on the power system representing the transient modes include the change of the generating power, the change of the load power, the voltage drop at the busses, the variation of the distributed power on the transmission line.

The input data is classified into two steady/unstable states based on observing the relationship between the power angles of the generators on the power system. The output data represents whether the state of the power system is stable or unstable.

2.2. DSP model building

The process of building a DSP model is carried out in detail in Figure 1.

2.2.1. Input data

The input data is classified into two steady/unstable states based on observing the relationship between the power angles of the generators on the power system. The standards for evaluating stability are:

$$\begin{cases} if\ \Delta\delta_{ij} \le 180^o\ stability \\ if\ \Delta\delta_{ij} > 180^o\ unstability \end{cases} \quad (1)$$

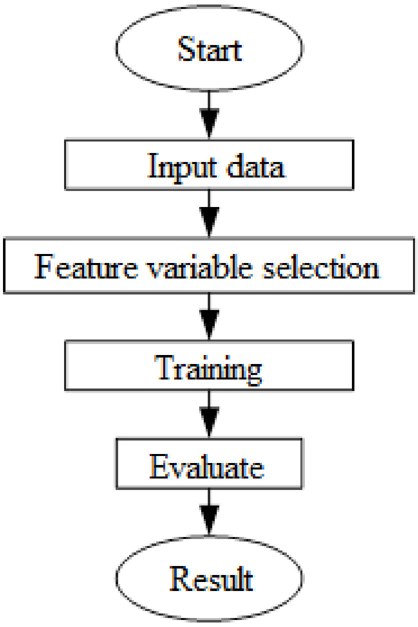

Figure 1. DSP model building process.

The states that characterize the operating state of the system are called samples, each sample is represented as a vector consisting of a number of characteristic variables represented as follows (Vo Thanh An, 2016):

$$Z_j = [V_{bus}, P_{load}, P_{flow}] \quad (2)$$

Input data will be normalized before training and calculated according to formula (3).

$$Z_j = \frac{x_j - m_j}{\delta_j} \quad (3)$$

With: x_i, z_i is the initial value, and the normalized value of the *i*, m_i feature variable is the mean of the data, σ_i the standard variance of the data.

2.2.2. Feature variable selection

Select feature variables to eliminate irrelevant variables and/or redundant variables without affecting learning performance. There are many methods for selecting feature variables such as: Fisher distance function, Divergence distance function, Relief algorithm, etc. The article applies the Relief variable selection algorithm. (Phan Viet Thinh, 2015).

2.3.3. Training

In order to train and test the diagnostic model objectively and generally, the training dataset is randomly divided into training data set (75%), test dataset (25%).

The problem applies MLPNN (Multilayer Perceptron Neural Network) 3 layers with 1 input layer, 1 hidden layer and 1 output layer (Zhang et al., 2021). In Matlab, the newff network function code is called according to the following syntax: *net = newff(p,t,n);*

The output is normalized according to the law (4). If the output encoding {1} is stable, and {0} is unstable, then:

$$\begin{cases} if\,\Delta\delta_{ij} > 0.5 \rightarrow y = 1 : stability \\ if\,\Delta\delta_{ij} \leq 0.5 \rightarrow y = 0 : unstability \end{cases} \qquad (4)$$

2.2.4. Assessment of recognition accuracy

The percentage of the model's recognition accuracy in training or testing is averaged over k executions. The model's recognition accuracy was evaluated as percentage of correct training or correct test and determined by formula (5).

$$\%\text{Correct Classification} = \frac{R}{S} x\, 100\% \qquad (5)$$

Where: R is the total number of correct samples, S is the total number of samples.

2.3. Proposal of backup control (PDSC)

The working space of the power system is a collection of stable and unstable working points. These work points are divided into two regions as illustrated in Figure 2. In which the symbol $\oplus$ represents the stable working points, the symbol $\ominus$ represents the unstable working points. When the working space of the power system falls into a stable area, if there is a problem, the power system will still maintain a stable state. On the contrary, at the unstable working point, if a problem occurs, it will cause instability of the power system. Through observation, when the working space of the power system falls into the point of instability, it is possible to control the movement of the working space of the power system to the stable area, which will ensure the safety of the power system if the power system is damaged. The control of the working point to the stable region can be based on the stored stability data set. For the archival sample, the stable working point scenario has been predetermined, so the execution is fast.

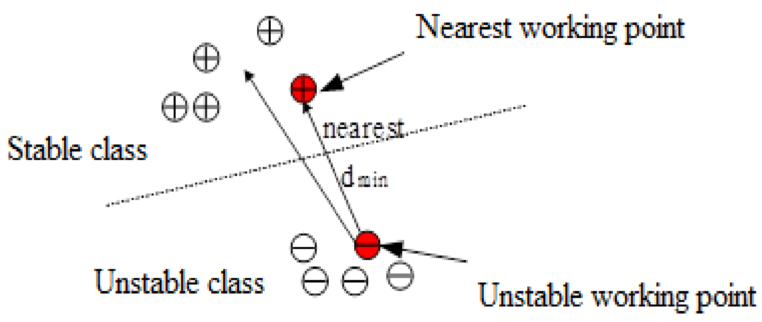

Figure 2. Illustrate the working point of the power system

2.3.1 Calculation area limit

The load graph fuzzy algorithm is used to limit the calculation area to find a stable working point in the sample area with the same transmit power level as the unstable point.

Membership function (x) : R→ [0,1] of the fuzzy number triangle defined on R then:

$$\tilde{M}_{(X)} = \begin{cases} \dfrac{x}{m-l} - \dfrac{l}{m-l}, ifx \in [l, m] \\ \dfrac{x}{m-u} - \dfrac{u}{m-u}, ifx \in [l, u] \\ 0, othercases \end{cases} \qquad (6)$$

Here: l and m are the best values of the fuzzy numbers M, l and u are the lower and upper bounds, respectively. According to Zadeh's extension principle for two fuzzy number triangles, Figure 3.

$$\tilde{M}_1 = (l_1, m_1, u_1) \text{ and } \tilde{M}_2 = (l_2, m_2, u_2) \qquad (l_1 \text{ và } l_2 \geq 0) \qquad (7)$$

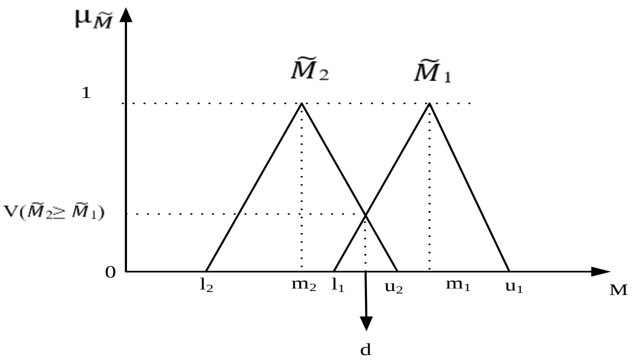

Figure 3. Competition model between $\tilde{M}_1, \tilde{M}_2$

2.3.2. Find a representative sample of the PDSC strategy

The problem of finding a stable working point has been limited to the sample area with the power level corresponding to the area of the original unstable working point. However, the number of stable samples corresponding to each power level is still large, so finding a stable working point takes a long time, which leads to a delay in making control decisions - PDSC. To solve the above problem, the method of reducing the sample is proposed. In this paper, the sample energy method is applied to divide the data into subgroups.

The energy level of sample E_i is calculated according to the following expression:

$$E_i = x_1^2 + x_2^2 + ... + x_n^2 \qquad (8)$$

After the energy levels for each sample were calculated, samples with similar energy levels were grouped together. Within each group, it is necessary to define a sample that is representative of the group. The representative sample is the group center or the sample with the average energy level of the group. For example in Figure 4, the dataset has 'm' samples divided into 2 groups, the average energy levels for the 2 groups are E_{D1} and E_{D2}. Therefore, the dataset with 'm' samples is reduced to 2 samples with energy levels E_{D1} and E_{D2}.

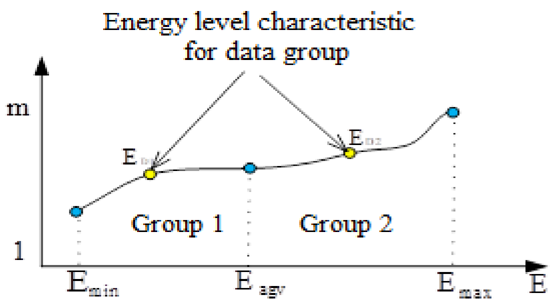

Figure 4. Split data by energy level

The sample set is divided by energy level, so finding a stable working point will be based on the energy level of the data. Specifically, if the unstable working point has a power level in any group, the working point of the PS will be shifted to the representative sample in that group.

3. Results – Discussion

3.1. Input data

The papper checks the accuracy of the model on a power system consisting of 4 generators - 10 buses (Gurrala & Sen, 2010; Uravakonda et al., 2022). The system consists of 4 generators, 4 transformers, 6 transmission lines and 2 loads. Four transmitters are connected from bus 1 to bus 4 where bus 2 is considered as Slack bus, remaining 3 generator buses are PV bus, 6 non-generator connected buses are PQ bus. PS has 2 different voltage levels, 230kV and 20kV. The system is given as shown in Figure 5.

The data is generated through off-line simulation on Matlab software, considering the balanced 3-phase short circuit at the inter-regional line with load levels of 90%, 100%, 110% of base load, with time Short circuit setting is 3 cycles after the short circuit. As a result, the data sample set includes 1845 stable samples and 1394 unstable samples, Data (1845,1394). The data is normalized before calculation according to formula (2).

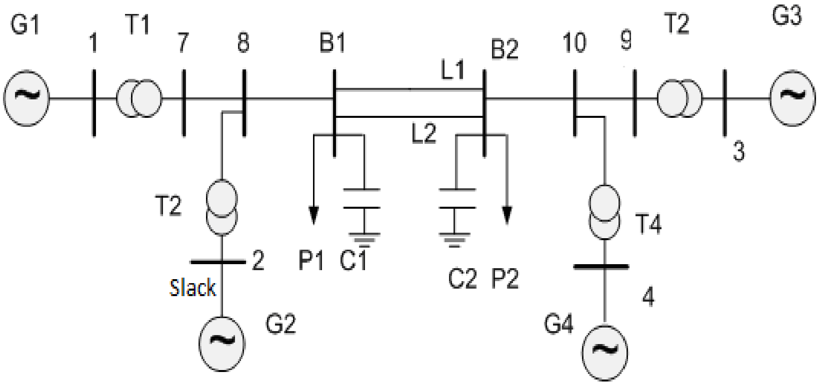

Figure 5. Model of power system with 4 generators – 10 bus

3.2. Feature variable selection

Variables are represented as vectors $x = [V_{bus}, P_{load}, P_{flow}]$. The total number of input variables is 22 variables including 10 voltage variables at the busses, 2 load active power variables, 4 transmitter active power variables and 6 active power variables distributed on the transmission line. The results of the variable rank calculation of the Relief method are presented in Figure 6.

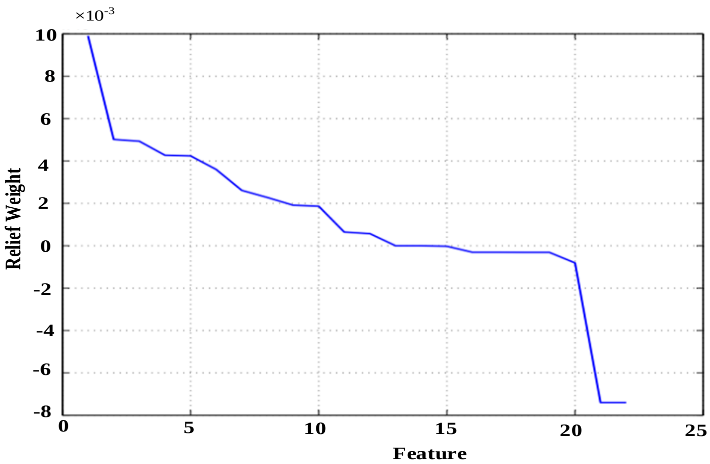

Figure 6. Variable Rank Relief Algorithm

Train by trial and error several times with different subsets of variables to find the best results. The percentage of diagnostic accuracy of the model in training or testing was averaged over 10 executions. The percentage of correct training or correct testing is determined by formula (4). The diagnostic accuracy for different variables is shown in Figure 7 and Table 1.

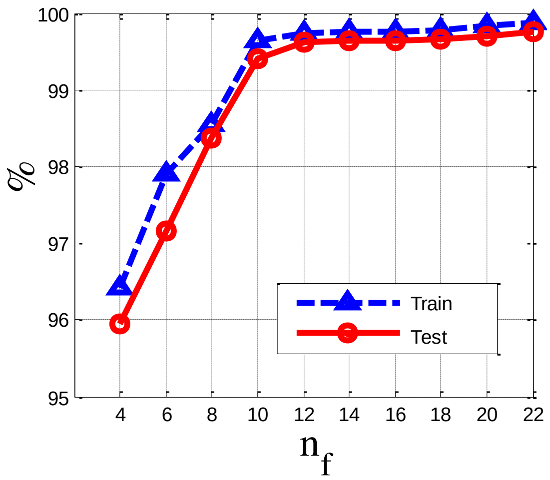

Figure 7. Results of variable selection evaluation.

From Figure 7 draw the results of evaluating the test accuracy of the model at the number of variables (nf) of 10 variables and 22 variables as shown in Table 1.

TABLE 1. Evaluation results at 10 and 22 variables.

Number of variables	10	22
Train (%)	99.6	99.8
Test (%)	99.4	99.7

3.3. Control Model (PDSC)

3.3.1 Limit the working area

To simplify the calculation, perform load graph fuzzy as suggested above. In which the sample set is divided into 3 groups, each group has a power level that fluctuates within ±5% of the base load. The results of load graph fuzzification are presented in Table 2. Assuming the load is operating at 103% of base load, the results show $\mu_2 > \mu_3$ so load level 2 is selected. The results of a stable sample set of 1845 samples divided into 3 levels are presented in Table 2.

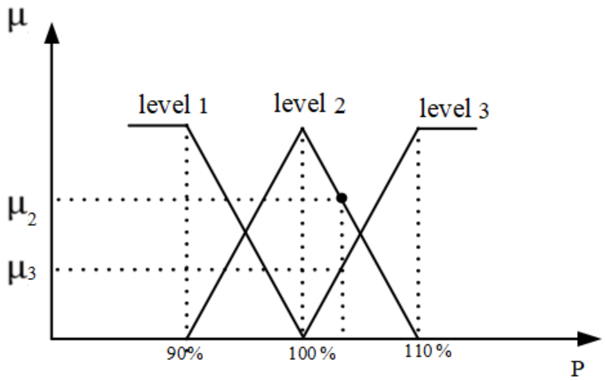

Figure 8. Fuzzy load graph

*TABLE 2***.** Calculation results of load graph fuzzification

Value % load	**Load levels**	**Sample number**
85%- 95%	Level 1 (90%)	720
95%-105%	Level 2 (100%)	666
105% - 115%	Level 3 (110%)	459

3.3.2 Find a representative sample of PDSC strategy

In order to reduce the computational volume, the problem uses the sample energy method to divide the data into groups. Applying the energy function for each load level, the energy of the data set is shown in the graph Figure 9.

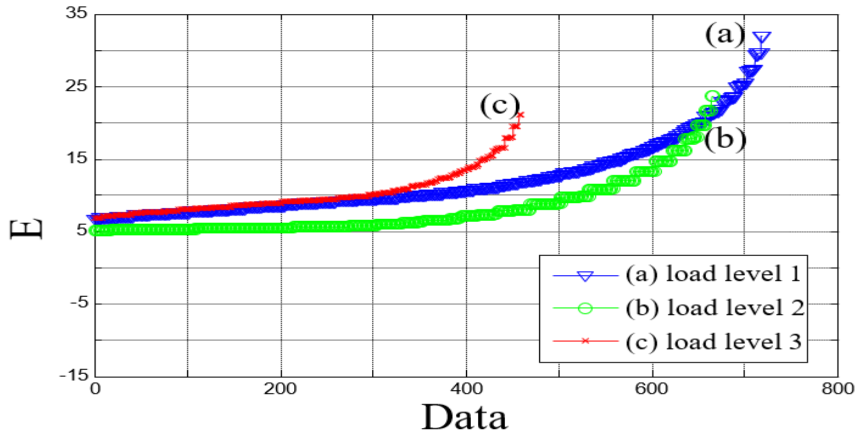

Figure 9. Energy distribution of 3 load level

The power at each load level after fuzzification of the load graph fluctuates within ±5% of the load level value. Based on this factor, the researcher divided the data set into two groups with the smallest, medium, and largest energy levels: group 1 ($E_{min} \le E_x \le E_{avg}$), group 2 ($E_{avg} < E_x \le E_{max}$). A representative sample of the data group shall be a sample with a large transmit power level sufficient to cover the control cases. Therefore, the representative sample of the data group will be the high-energy sample of the data group. Specifically, the results of grouping and selecting representative samples are presented in Table 3.

TABLE 3. Stability data group by load levels

Load levels		**Power level**	**Sample number**	**Energy level of representative sample**	
Load level 1 (90%)	Group 1	$6.76 \le E_i \le 19.4$	645	19.4	M_{S1}
	Group 2	$19.4 < E_i \le 31.9$	75	31.9	M_{S2}
Load level 2 (100%)	Group 3	$5.5 \le E_i \le 14.4$	604	14.4	M_{S3}
	Group 4	$14.4 < E_i \le 23.7$	62	23.7	M_{S4}
Load level 3 (110%)	Group 5	$6.9 \le E_i \le 14.0$	412	14.0	M_{S5}
	Group 6	$14.0 < E_i \le 21.1$	47	21.1	M_{S6}

After the process of blurring the load graph and finding a representative sample for the PDSC control strategy, the result of the stable sample set SS(1845) was reduced to 6 samples representing the control scenario. In order to facilitate the evaluation of PDSC control strategy, for each load level, it is proposed to select three unstable representative samples with energy levels (max, avg, min) or a total of 9 samples. represent. The energy levels of the samples are shown in Table 4.

TABLE 4. Unstable Samples of 3 Load Levels

Load levels	Power level	
Load level 1 (90%)	$M1_{max}$	29.2
	$M1_{avg}$	15.22
	$M1_{min}$	6,63
Load level 2 (100%)	$M2_{max}$	22.62
	$M2_{avg}$	13.21
	$M2_{min}$	5.1
Load level 3 (110%)	$M3_{max}$	20.91
	$M3_{avg}$	13.56
	$M3_{min}$	6.81

Table 4 presents 9 unstable samples representing the joystick about 6 stable working points in Table 3. The control calculation strategy is shown in Table 5 for 9 unstable samples. Figure 10 illustrates a case where the working point is unstable at Load Level 1 with the energy M_{1max} of the power system being shifted to the stable point with the fault occurring.

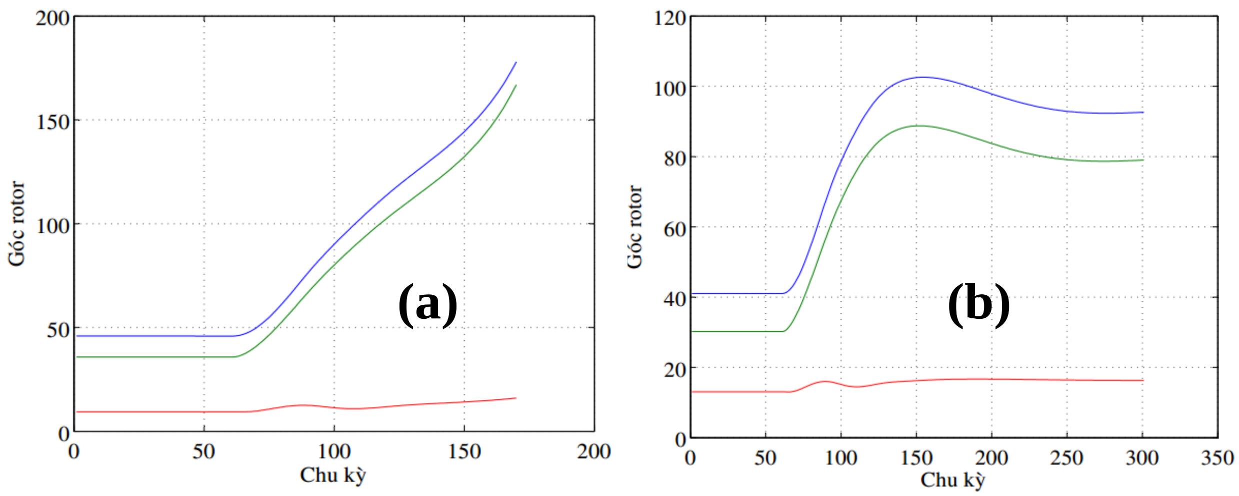

Figure 10. Rotor deflection angle (a) when not controller, (b) when controller

TABLE 5. Preventive control results

Before the controller		After controller	
Unstable working point	**Total active power (MW)**	**Working point teleports to**	**Total active power (MW)**
$M1_{min}$	2546	M_{S1}	2550
$M1_{avg}$	2571		2575
$M1_{max}$	2600	M_{S2}	2630
$M2_{min}$	2656	M_{S3}	2661
$M2_{avg}$	2784		2793
$M2_{max}$	2823	M_{S4}	2830
$M3_{min}$	2868	M_{S5}	2890
$M3_{avg}$	2946		2953
$M3_{max}$	2970	M_{S6}	3018

3.4. Discussion

Table 1 and Figure 7, the number of input variables is 10, the test accuracy result is 99.4%. Compared with the original 22 variables, this result shows that the number of variables decreased by 54% while the accuracy decreased by only 0.3%. The paper applies sample energy and fuzzy law to limit the working area for preventive control. The results presented in Tables 4 and 5 show that with the initial unstable sample space of 1394 samples represented only 9 samples, 1845 stable samples represented only 6 samples. This has great significance in compacting the search for control space, reducing sample memory storage space. Figure 10 shows the effectiveness of applying the proposed control strategy to save the PS from being destabilized when the problem occurs.

4. Conclusion

The study proposed a preventive operating and control mode based on the results of dynamic security prediction for the power system. The simulation model and input data are taken from IEEE standard 10 node-4 generators network parameters. The idea is based on sample energy and fuzzy rules to limit the stable working point of the electromagnetic system so that the operator can propose the optimal control mode. Testing with different load levels (90%, 100%, 110%) on the IEEE model shows that the proposed control mode has the effect of continuously stable power system operation. Research results also show effectiveness in compacting sample memory storage space.

This research helps power system operators come up with appropriate operating modes and predict the stability of the power system even when an incident occurs.

References

Andersson, G., Donalek, P., Farmer, R., Hatziargyriou, N., Kamwa, I., Kundur, P., Martins, N., Paserba, J., Pourbeik, P., Sanchez-Gasca, J., Schulz, R., Stankovic, A., Taylor, C., & Vittal, V. (2005). Causes of the 2003 major grid blackouts in North America Europe, and recommended means to improve system dynamic performance. *IEEE Transactions on Power Systems*, *20*(4), 1922-1928. https://doi.org/10.1109/TPWRS.2005.857942

Bento, M. E. C. (2024). Physics-Guided Neural Network for Load Margin Assessment of Power Systems. *IEEE Transactions on Power Systems*, *39*(1), 564-575. https://doi.org/10.1109/TPWRS.2023.3266236

Furse, C. M., Kafal, M., Razzaghi, R., & Shin, Y. J. (2021). Fault Diagnosis for Electrical Systems and Power Networks: A Review. *IEEE Sensors Journal*, *21*(2), 888-906. https://doi.org/10.1109/JSEN.2020.2987321

Gurrala, G., & Sen, I. (2010). Power system stabilizers design for interconnected power systems. *IEEE Transactions on Power Systems*, *25*(2), 1042-1051. https://doi.org/10.1109/TPWRS.2009.2036778

Makarov, Y. V., Reshetov, V. I., Stroev, V. A., & Voropai, N. I. (2005). Blackout prevention in the United States, Europe, and Russia. *Proceedings of the IEEE*, *93*(11), 1942-1954. https://doi.org/10.1109/JPROC.2005.857486

Maraaba, L., Almuhaini, M., Habli, M., & Khalid, M. (2023). Neural Networks Based Dynamic Load Modeling for Power System Reliability Assessment. *Sustainability*, *15*(6), 5403. https://doi.org/10.3390/SU15065403

Phan Viết Thịnh (2015). *Power system stability analysis and control* (Master thesis). [Phân tích và Điều khiển Ổn định hệ thống điện]. HCMC University of Technology and Education.

Uravakonda, S., Mallapu, V. K., & Reddy, V. R. A. (2022). An analytical approach for LQR design for improving damping performance of multi-machine power system. *Indonesian Journal of Electrical Engineering and Computer Science*, *25*(1), 51-58. https://doi.org/10.11591/IJEECS.V25.I1.PP51-58

Võ Thành An (2016). *Research on methods to identify power system stability* (Master thesis). [Nghiên cứu các phương pháp nhận dạng ổn định hệ thống điện], HCMC University of Technology and Education.

Wazirali, R., Yaghoubi, E., Abujazar, M. S. S., Ahmad, R., & Vakili, A. H. (2023). State-of-the-art review on energy and load forecasting in microgrids using artificial neural networks, machine learning, and deep learning techniques. *Electric Power Systems Research*, *225*, 109792. https://doi.org/10.1016/J.EPSR.2023.109792

Zhang, H., Shen, S., & Shen, Y. (2021). Power System Transient Stability Evaluation Based on Multilayer Perceptron Neural Network. *Proceeding - 2021 China Automation Congress, CAC 2021*, 3313-3316. https://doi.org/10.1109/CAC53003.2021.9727444