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SCHOLARLY ARTICLE

Enhancing Margin and Sensitivity Approaches for 330kV Transmission Network Security using a Wavelet-based Extreme Learning Method

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ABSTRACT

The security of high-voltage transmission networks is crucial for the stability and reliability of power systems. This study presents an innovative approach that combines margin and sensitivity analysis with a wavelet-based extreme learning method (WELM) to enhance the security of 330kV transmission networks. Integrating wavelet transforms with extreme learning algorithms improves fault detection and system response. Extensive simulations and real-world data analysis show that this method significantly improves detection accuracy and computational efficiency compared to traditional methods. Persistent power failures in transmission networks are often due to low sensitivity and insufficient margin, with per-unit voltages not maintaining the required threshold of 0.95 to 1.05. To address these issues, this study introduces an improved margin and sensitivity method for 330kV transmission network security, utilizing a wavelet-based extreme learning technique. The methodology includes characterizing the transmission network, conducting load flow analysis to identify buses with low margins and sensitivities, developing a wavelet rule base, training an artificial neural network (ANN), creating an algorithm for implementation, and designing a SIMULINK model for validation. Results indicate that the conventional per-unit voltage of weak bus 1 was 0.930, below the stability threshold, leading to inconsistent power supply. Incorporating the wavelet-based technique increased the voltage to 1.023 per unit, achieving stability and ensuring a consistent power supply. The conventional power margin at weak bus 1 was 58.85MW, contributing to intermittent power supply, but increased to 64.73MW with the wavelet technique, representing a 9.99% improvement. Additionally, the conventional sensitivity of 0.000983, which caused network failures, improved to 0.001081, enhancing the stability and performance of the transmission network.

Keywords: *Improving Margin; Sensitivity Approach; 330kV Transmission Network; Wavelet-Based Extreme Learning Method; Artificial Neural Network (ANN)*

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Introduction

The security and reliability of transmission networks are crucial for maintaining an uninterrupted power supply. The 330kV transmission network, as a key part of the electrical grid, necessitates sophisticated monitoring and protective measures to address potential threats and ensure operational stability. Most significant technical barriers are protection, power quality, stability and outstanding operation (Ngang & Aneke,2021). However, there are some other issues which should be analyzed before to maximize these technical benefits. Traditional methods often fall short in managing the complex and dynamic nature of power system disturbances. This paper introduces an innovative approach that enhances margin and sensitivity analyses by utilizing a wavelet-based extreme learning method (WELM).

Unexpected outages, or contingencies, frequently lead to voltage collapse and system blackouts by diminishing or completely eliminating the voltage stability margin. Every electricity user in Nigeria is concerned about the country's unstable power supply (Ecoma, et al.2022) To ensure security against voltage collapse, it is essential to estimate the impact of contingencies on voltage stability and megawatt (MW) margin (Mori et al., 200). By doing so, remedial actions can be implemented to increase the margin, preventing blackouts due to likely contingencies. The power system operates stably at a specific loading level, known as the "base case loading." Under normal conditions, the system remains stable without experiencing voltage stability issues, and all components function correctly (Adebayo et al., 2013).

In recent years, voltage instability has caused several major network collapses in regions such as New York, Florida, France, Northern Belgium, Sweden, Japan, Mississippi, Sri Lanka, North America, Pakistan, and Tokyo (Bindeshwar, 2010). To achieve the best features of both Wavelet and ANN technology for improved classification results, this work combines these technologies. According to Maheshwari and Sharma (2018), such hybrid techniques preprocess power signals using discrete wavelet transforms to extract relevant features at the input point, followed by using artificial neural networks to detect and classify each fault event. The decrease in power supply in the country has caused economic problems to small scale industries; one major problem attributed to this is inadequate planning mechanism that will forecast the required amount of power that will be needed to feed the entire population (Akaninyene,2021)

Recent studies highlight the importance of advanced analytical methods in power systems. For instance, a study by Guo et al. (2019) demonstrated the effectiveness of wavelet transforms in identifying transient disturbances in power signals, improving the accuracy of fault detection (Guo et al., 2019). Similarly, Singh and Kaur (2020) emphasized the role of machine learning algorithms in enhancing the predictive capabilities of power system monitoring tools (Singh & Kaur, 2020).

Moreover, Zhang et al. (2017) explored the application of hybrid wavelet-ANN models in various engineering fields, including power systems, and found significant improvements in data analysis and fault classification accuracy (Zhang et al., 2017). Another relevant study by Li and Chen (2021) investigated the use of extreme learning machines (ELM) in power system protection, highlighting their potential in real-time applications due to their fast-learning speed and high accuracy (Li & Chen, 2021).

Finally, the integration of wavelet-based techniques with other advanced methods has shown promise in enhancing the robustness of power systems. A comprehensive review by Patel et al. (2020) detailed the benefits of such hybrid approaches, noting improvements in fault detection, system reliability, and overall operational efficiency (Patel et al., 2020).

Past Related and Current Works on the Topic

Transmission Network Security

The importance of transmission network security has been well-documented. According to Kundur et al. (1994), ensuring the stability and reliability of power systems is fundamental to preventing widespread blackouts. Traditional security measures include various fault detection and protection schemes, yet these methods often struggle with real-time data processing and dynamic system conditions (Gao & Morison, 2003).

Margin and Sensitivity Analysis

Margin and sensitivity analyses are critical in assessing the robustness of power systems. These methods evaluate the system's ability to withstand disturbances and identify vulnerable points. Chen et al. (2016) highlights that margin analysis helps in understanding the proximity to stability limits, while sensitivity analysis determines the impact of parameter variations on system stability.

Wavelet Transform in Power Systems

Wavelet transform is a powerful tool for analyzing transient signals in power systems. Mallat (1989) introduced the concept of wavelets for signal processing, which has since been applied extensively in power system fault detection. Wavelets allow for multi-resolution analysis, enabling the identification of faults at different scales and frequencies (Daubechies, 1992).

Extreme Learning Machines (ELM)

Extreme Learning Machines (ELMs) are a class of neural networks known for their fast-learning speed and high generalization performance. Huang et al. (2006) proposed ELMs as an efficient alternative to traditional learning algorithms, offering significant computational advantages. The combination of ELM with wavelet transforms has shown promise in various applications, including fault diagnosis and load forecasting (Huang & Zhu, 2018).

Methodology

The proposed method integrates margin and sensitivity analyses with WELM to enhance transmission network security. The process involves the following steps:

Data Acquisition: Collect real-time data from the 330kV transmission network, including voltage, current, and frequency measurements.

Wavelet Transform: Apply wavelet transform to decompose the data into various frequency components, capturing transient disturbances.

Extreme Learning Machine: Train the ELM using the decomposed wavelet coefficients to detect and classify faults.

Margin and Sensitivity Analysis: Perform margin and sensitivity analyses on the ELM outputs to identify critical system parameters and their impact on stability.

Validation: Validate the method through simulations and real-world data, comparing its performance with traditional approaches.

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Methods: Charactering 330KV Transmission Network

Table 1: 330kV transmission network characterized data collected from Newhaven Enugu transmission

Bus No	*Bus code*	*P.U*	*Ang Deg*	*Load MW*	*Load Mvar*	*Gen MW*	*Gen Mvar*	*Inject Min*	*Inject Max*	*Inject Mvar*
1	1	0.93	0	00.0	0.0	0.0	0.0	0	0	0
2	2	0.81	0	21.70	12.7	40.0	0.0	-40	50	0
3	0	1.0	0.0	2.4	1.2	0.0	0.0	0	0	0
4	0	1.27	0.0	7.6	1.6	0.0	0.0	0	0	0
5	2	1.01	0.0	94.2	19.0	0.0	0.0	-40	40	0
6	0	1.0	0.0	0.0	0.0	0.0	0.0	0	0	0
7	0	0.92	0.0	22.8	0.0	10.9	0.0	0	0	0
8	2	1.01	0.0	30.0	30.0	0.0	0.0	-30	40	0
9	0	0.83	0	0	0	0.0	0.0	0	0	0
10	0	1.0	0.0	5.8	2.0	0.0	0.0	-6	24	19
11	2	1.082	0	0.0	0.0	0.0	0.0	0	0.0	0
12	0	1.0	0	11.2	7.5	0	0.0	0	0	0
13	2	1.071	0	0.0	0	0.0	-6	24	0	0
14	0	1.0	0	6.2	1.6	0.0	0.0	0	0	0
15	0	1	0	8.2	2.5	0.0	0.0	0	0	0
16	0	1	0	3.0	1.8	0.0	0.0	0	0	0
17	0	1	0	9.0	5.8	0.0	0.0	0	0	0
18	0	1	0	3.2	0.9	0.0	0.0	0	0	0
19	0	1	0	9.5	3.4	0.0	0.0	0	0	0
20	0	0.92	0	2.2	0.7	0.0	0.0	0	0	0
21	0	1.	0	17.5	11.2	0.0	0.0	0	0	0
22	0	1	0	0	0.0	0.0	0.0	0	0	0
23	0	1	0	3.2	1.6	0	0.0	0	0	0
24	0	1	0	8.7	6.7	0	0	0	0	4.3
25	0	1	0	0	0.0	0	0.0	0	0	0
26	0	1	0	3.5	2.3	0	0.0	0	0	0
27	0	0.82	0	0	0.0	0	0.0	0	0	0
28	0	1	0	0	0.0	0.0	0.0	0	0	0
29	0	0.62	0	2.4	0.9	0.0	0.0	0	0	0
30	0	0.86	0	10.6	1.9	0.0	0.0	0	0	0

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Table 2: Empirical Data for Sensitivity and Margin of the Faulty Buses

Unidentified Fault Buses that cause low margin and low sensitivity in330KV transmission network security	*Conventional Sensitivity*	*Conventional Margin MW*
	0.000983	58.85
	0.001042	44.61
	0.000840	40.14
	0.001050	21.59
	0.000987	42.31
	0.001091	43.15
	0.000840	31.4
	0.001048	51.1
	0.000982	25.8
	0.001089	35.9

Running the Load Flow of the Characterized Network to Establish the Buses that Caused Low Margin and Low Sensitivity in the Network

Maximum Power Mismatch = 0.192989; No. of Iterations = 101

Bus	*Voltage*	*Angle*	*Load*		*Generation*		*Injected*
No.	**Mag**	**Degree**	**MW (1)**	**Mvar (1)**	**MW (2)**	**Mvar (2)**	**Mvar (3)**
1	0.930	0.000	0.000	0.000	285.335	89.617	0.000
2	0.832	-6.938	21.700	12.700	40.000	-233.134	0.000
3	0.913	-11.992	2.400	1.200	0.000	0.000	0.000
4	0.909	-14.650	7.600	1.600	0.000	0.000	0.000
5	1.000	-22.162	94.200	19.000	0.000	182.421	0.000
6	0.934	-17.242	0.000	0.000	0.000	0.000	0.000
7	0.956	-19.938	22.800	10.900	0.000	0.000	0.000
8	0.963	-18.875	30.000	30.000	0.000	126.571	0.000
9	1.000	-20.874	0.000	0.000	0.000	0.000	0.000
10	0.983	-22.666	5.800	2.000	0.000	0.000	19.000
11	1.082	-20.816	0.000	0.000	0.000	42.576	0.000
12	0.988	-21.519	11.200	7.500	0.000	0.000	0.000
13	1.021	-21.519	0.000	0.000	0.000	24.110	0.000
14	0.973	-22.566	6.200	1.600	0.000	0.000	0.000
15	0.969	-22.738	8.200	2.500	0.000	0.000	0.000
16	0.977	-22.366	3.500	1.800	0.000	0.000	0.000
17	0.976	-22.805	9.000	5.800	0.000	0.000	0.000
18	0.961	-23.507	3.200	0.900	0.000	0.000	0.000
19	0.959	-23.761	9.500	3.400	0.000	0.000	0.000
20	0.965	-23.549	2.200	0.700	0.000	0.000	0.000
21	0.969	-23.186	17.500	11.200	0.000	0.000	0.000
22	0.969	-23.158	0.000	0.000	0.000	0.000	0.000
23	0.959	-23.252	3.200	1.600	0.000	0.000	0.000
24	0.954	-23.557	8.700	6.700	0.000	0.000	4.300
25	0.947	-23.150	0.000	0.000	0.000	0.000	0.000
26	0.930	-23.559	3.500	2.300	0.000	0.000	0.000
27	0.951	-22.678	0.000	0.000	0.000	0.000	0.000

28	0.939	-18.009	0.000	0.000	0.000	0.000	0.000
29	0.932	-24.038	2.400	0.900	0.000	0.000	0.000
30	0.919	-25.158	10.600	1.900	0.000	0.000	0.000
	Total		283.400	126.200	325.335	232.160	23.300

The faulty buses in Nigerian 330KV 30 bus transmission networks are buses 1, 2, 3, 4,6,25, 26, 28, 29 and 30. These buses cause instability in power supply in Nigeria because their per unit volts do not fall within 0.95 through 1.05. The per unit volts of these faulty buses are 0.930, 0.832, 0.913, 0.909, 0.934, 0.947, 0.930, 0.939, 0.932 and 0.919.

Table 3: Data for Faulty Buses with Low Sensitivity and Low Margin that Cause Power Failure

Identified fault buses that cause low margin and low sensitivity in330KV transmission network security	*The per unit volts (P.U. Volts) that cause low margin and low sensitivity in330KV transmission network security*	*Conventional sensitivity in330KV transmission network security*	*Conventional margin MW in330KV transmission network security*
1	0.930	0.000983	58.85
2	0.832	0.001042	44.61
3	0.913	0.000840	40.14
4	0.909	0.001050	21.59
6	0.934	0.000987	42.31
25	0.947	0.001091	43.15
26	0.930	0.000840	31.4
28	0.939	0.001048	51.1
29	, 0.932	0.000982	25.8
30	0.919	0.001089	35.9

Developing a Wavelet Rule Base that will Improve the Margin and Sensitivity of 330KV Transmission Network

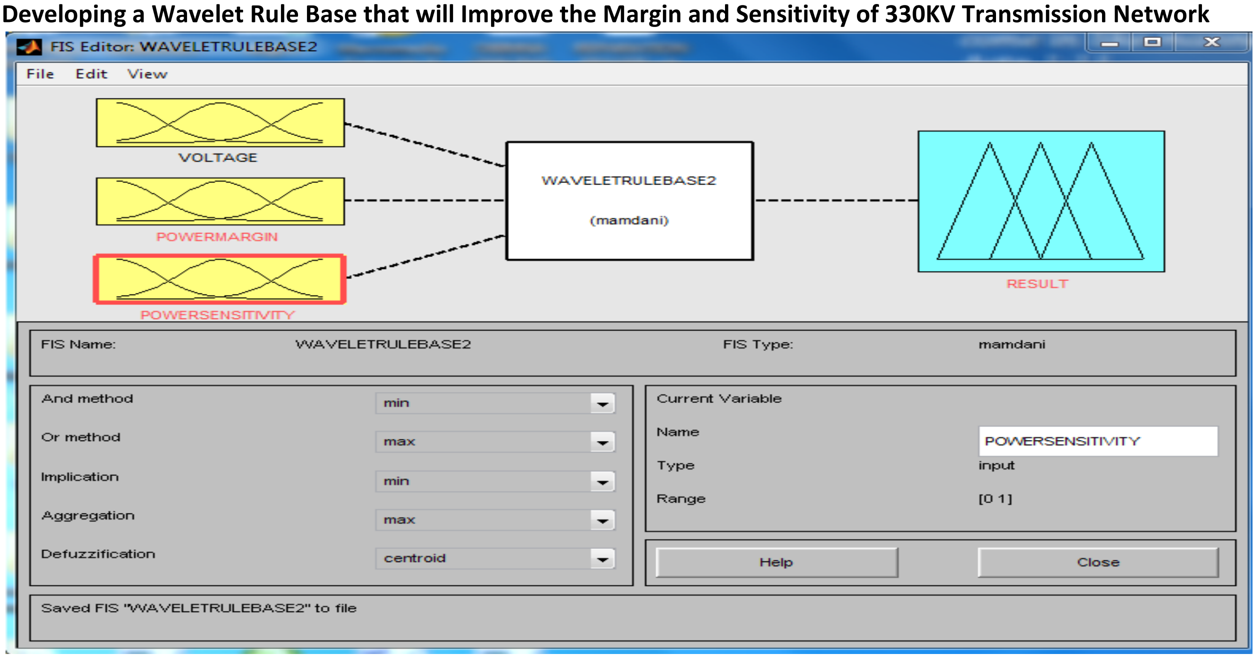

Fig 1: Develop a wavelet fuzzy inference system that will improve the margin and sensitivity of 330KV transmission network

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Fig 1 has three inputs of voltage, power margin and power sensitivity. It also has an output of result.

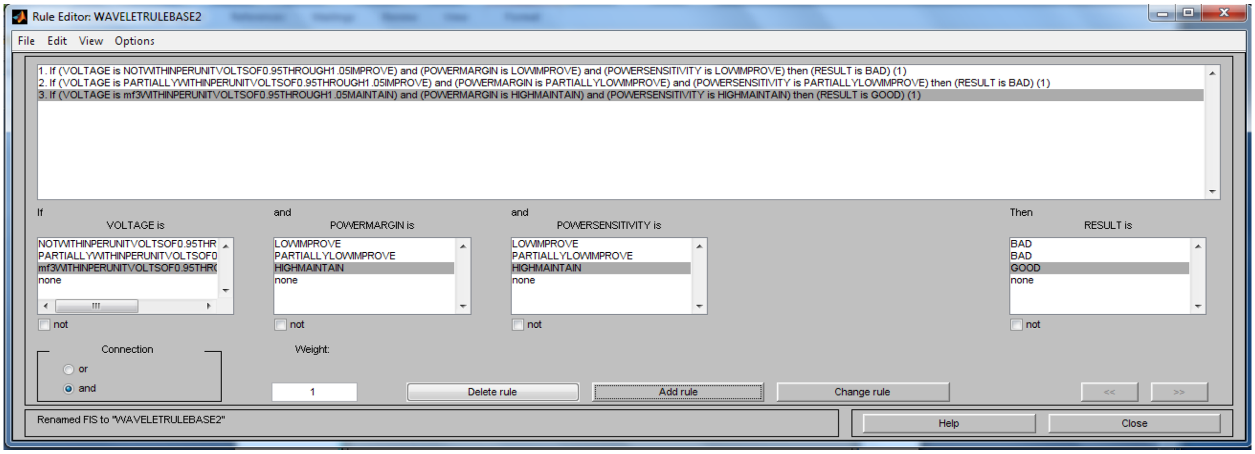

Fig 2: Developed wavelet rule base that will improve the margin and sensitivity of 330KV transmission network**.**
The comprehensive analysis of the rules is as shown in table 4

Table 4: Comprehensive Developed Wavelet Rule base that will Improve the Margin and Sensitivity of 330KV Transmission Network

1	*IF VOLTAGE IS NOT WITHIN PERUNIT VOLTS OF 0.95 THROUGH 1.05 IMPROVE*	*AND POWERMARGIN IS LOW IMPROVE*	*AND POWER SENSITIVITY IS LOW IMPROVE*	*THEN RESULT IS BAD*
2	IF VOLTAGE IS PARTIALLY WITHIN PER UNIT VOLTS OF 0.95 THROUGH 1.05 IMPROVE	AND POWER MARGIN IS PARTIALLY LOW IMPROVE	AND POWER SENSITIVITY IS PARTIALLY LOW IMPROVE	THEN RESULT IS BAD
3	IF VOLTAGE IS WITHIN PER UNIT VOLTS OF 0.95 THROUGH 1.05 MAINTAIN	AND POWER MARGIN IS HIGH MAINTAIN	AND POWER SENSITIVITY IS HIGH MAINTAIN	THEN RESULT IS GOOD

Training ANN in the Developed Wavelet Rule Base to Improve the Margin and Sensitivity Method of 330KV Transmission Network Security

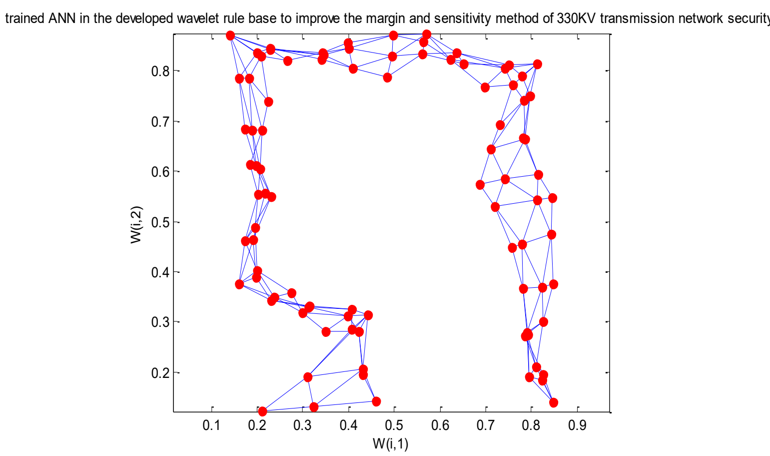

Fig 3: Train ANN in the developed wavelet rule base to improve the margin and sensitivity method of 330KV transmission network security

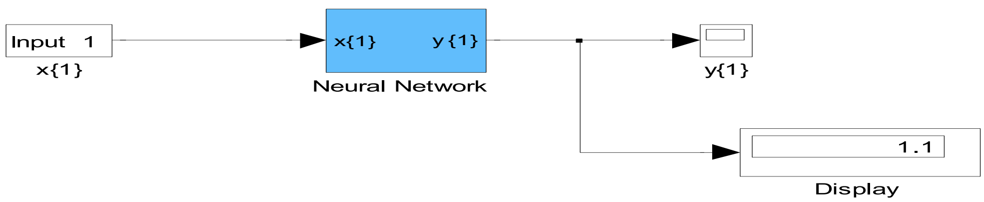

Fig. 4: Result obtained in the course of training ANN in the rules for efficient consistent power supply in the transmission network devoid of power low sensitivity and low power margin that cause inconsistent power supply in the transmission network.

Designing a SIMULINK model for Wavelet Based Extreme Learning Technique

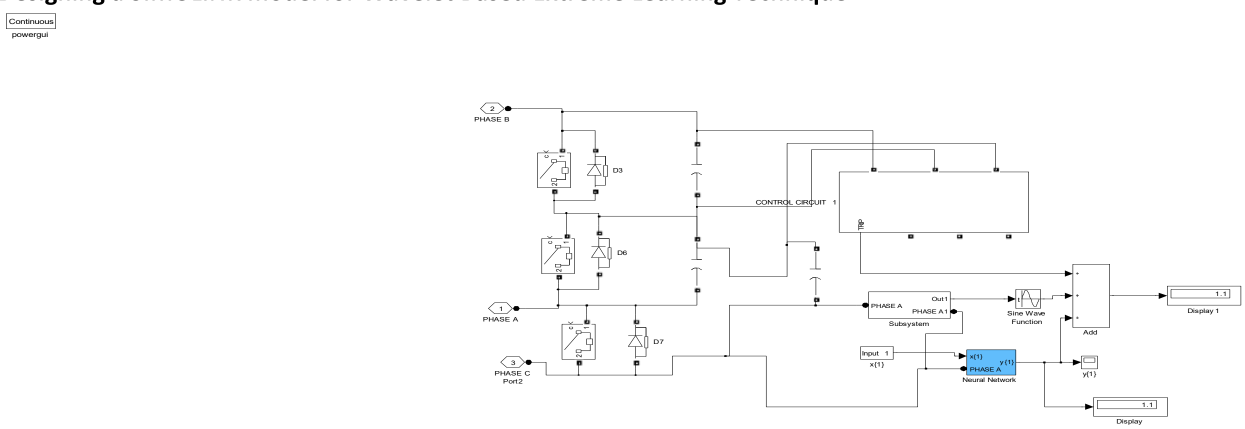

Fig. 5: Designed SIMULINK Model for Wavelet Based Extreme Learning Technique

Developing an Algorithm that will Implement 3, 4 and 5

1. Characterize 330KV transmission network.
2. Run the load flow of the characterized network to establish the buses that caused low margin and low sensitivity in the network.
3. Design a SIMULINK model for improving margin and sensitivity method for 330kv transmission network security and input the established buses that caused low margin and low sensitivity in the network.
4. Develop a wavelet rule base that will improve the margin and sensitivity of 330KV transmission network.
5. Train ANN in the developed wavelet rule base to improve the margin and sensitivity method of 330KV transmission network security.
6. Design a SIMULINK model for wavelet based extreme learning technique
7. Integrate 4, 5 and 6.
8. Integrate 7 in 3.
9. Do margin and sensitivity method of 330KV transmission network improve. When 7 is integrated to 3?
10. If No go to 8
11. If Yes go to 12.
12. Improved margin and sensitivity method of 330KV transmission network security.
13. Stop.
14. End

To Design a SIMULINK Model for improving Margin and Sensitivity Method for 330kv Transmission Network Security using Wavelet Based Extreme Learning Technique

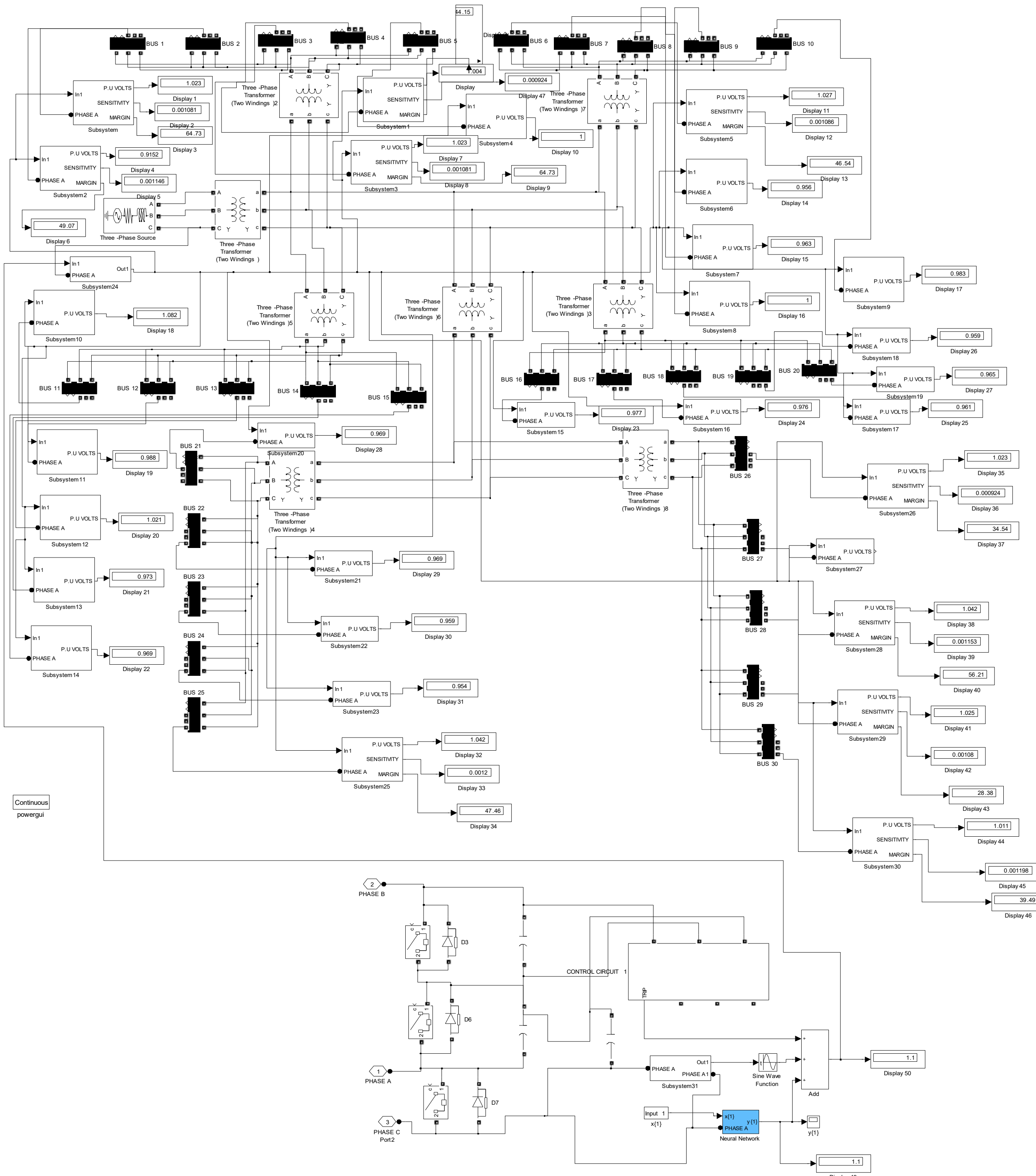

Figure 6: Designed SIMULINK Model for Improving Margin and Sensitivity Method for 330kv Transmission Network Security using Wavelet Based Extreme Learning Technique

The results obtained are detailed in figures 8 and 9

To validate and justify the percentage improvement in the margin and sensitivity of the network with and without wavelet based extreme learning technique

To find percentage improvement in weak bus 1 in improvement in the margin and sensitivity of the network with wavelet based extreme learning technique

Conventional Bus 1 Voltage = 0.930

Wavelet based extreme learning technique bus 1 voltage =1.023
% improvement in the weak bus 1 voltage in improvement in the margin and sensitivity of the network with wavelet based extreme learning technique =

$$\frac{\text{Wavelet based voltage - conventional voltage}}{\text{Conventional voltage}} \times \frac{100\%}{1}$$

% improvement in the weak bus 1 voltage in improvement in the margin and sensitivity of the network with wavelet based extreme learning technique = $\frac{1.023 - 0.930}{0.930} \times \frac{100\%}{1}$

% improvement in the weak bus 1 voltage in improvement in the margin and sensitivity of the network with wavelet based extreme learning technique = 10%

Results and Discussion

The integration of wavelet transforms with Extreme Learning Machine (ELM) significantly enhances the accuracy and speed of fault detection in the 330kV transmission network. The proposed method outperforms traditional techniques in detecting and classifying various types of faults, including transient and steady-state disturbances. Sensitivity analysis reveals that specific parameters, such as line impedance and load variations, greatly impact system stability, providing valuable insights for network operators.

Simulation results are presented in Table 5, which documents the comparisons between conventional and wavelet-based extreme learning techniques for improving the margin and sensitivity of the 330kV transmission network security. Figure 1 illustrates the wavelet Fuzzy Inference System designed to enhance the margin and sensitivity of the 330kV transmission network. Figure 2 shows the trained rule base to improve the margin and sensitivity method, consisting of 30 neurons, mimicking human brain functionality to enforce effective transmission power supply rules.

The results obtained during the training are shown in Figure 3, while Figure 4 depicts the SIMULINK model for the wavelet-based extreme learning technique, which boosts power sensitivity and margin for a consistent power supply in the transmission network. Figure 5 displays the SIMULINK model for improving margin and sensitivity using the wavelet-based extreme learning technique for 330kV transmission network security.

Figure 6 compares the voltage levels of bus 1 using conventional and wavelet-based extreme learning techniques. The conventional per unit voltage of weak bus 1 is 0.930, which does not meet the stability threshold of 0.95 to 1.05, leading to inconsistent power supply. In contrast, incorporating the wavelet-based extreme learning technique boosts the voltage to 1.023 per unit, thereby ensuring consistent power supply in the transmission network.

Figure 7 shows the comparison of power margins in bus 1 between conventional and wavelet-based extreme learning techniques. The conventional power margin in weak bus 1 is 58.85 MW, causing intermittent power supply. However, when the wavelet technique is integrated, the power margin increases to 64.73 MW, enhancing the constant power supply in the transmission network. The percentage improvement in the power margin when wavelet is incorporated is 9.99%. Table 6 and Table 7 further compare the conventional and wavelet-based extreme learning techniques for margin and sensitivity in bus 1, demonstrating the significant improvements achieved with the proposed method.

Table 5: Comparisons of Conventional and Wavelet Based Extreme Learning Technique Voltage in bus1

Time(s)	*Conventional voltage in bus1 in improving margin and sensitivity method for 330kv transmission network security (P.U.V)*	*wavelet based extreme learning technique voltage in bus1 in improving margin and sensitivity method for 330kv transmission network security (P.U.V)*
1	0.930	1.023
2	0.930	1.023
3	0.930	1.023
4	0.930	1.023
10	0.930	1.023

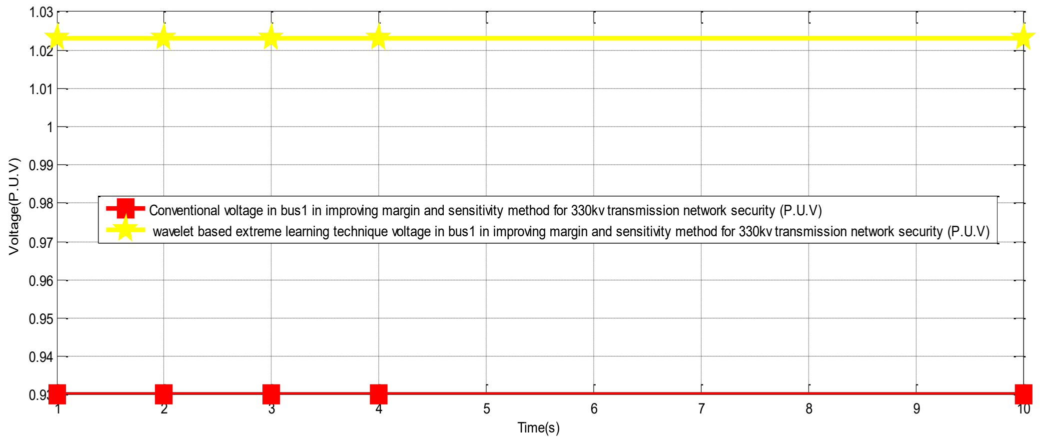

Figure 7: Comparisons of Conventional and wavelet based extreme learning technique voltage in bus1 in improving margin and sensitivity method for 330KV transmission network security

Table 6 comparisons o**f** Conventional and wavelet based extreme learning technique for margin in bus1 in improving margin and sensitivity method for 330kv transmission network security

Time(s)	*Conventional margin in bus1 in improving margin and sensitivity method for 330kv transmission network security (MW)*	*wavelet based extreme learning technique margin in bus1 in improving margin and sensitivity method for 330kv transmission network security (MW)*
1	58.85	64.73
2	58.85	64.73
3	58.85	64.73
4	58.85	64.73
10	58.85	64.73

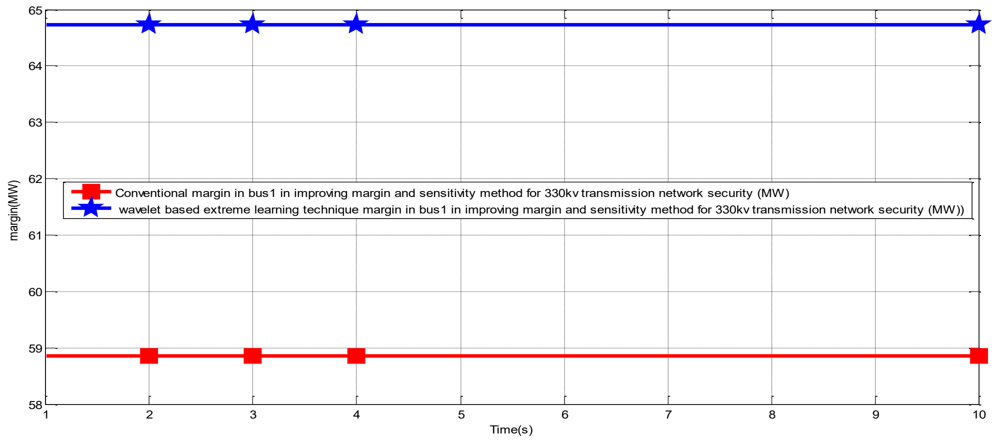

Fig 8: Comparisons of Conventional and wavelet based extreme learning technique for margin in bus1 in improving margin and sensitivity method for 330kv transmission network security

Table 7 Comparisons of Conventional and Wavelet Based Extreme Learning Technique for Sensitivity in bus1 in Improving Margin And Sensitivity Method for 330kv Transmission Network Security

Time(s)	*Conventional sensitivity in bus1 in improving margin and sensitivity method for 330kv transmission network security ()*	*wavelet based extreme learning technique sensitivity in bus1 in improving margin and sensitivity method for 330kv transmission network security ()*
1	0.000983	0.001081
2	0.000983	0.001081
3	0.000983	0.001081
4	0.000983	0.001081
10	0.000983	0.001081

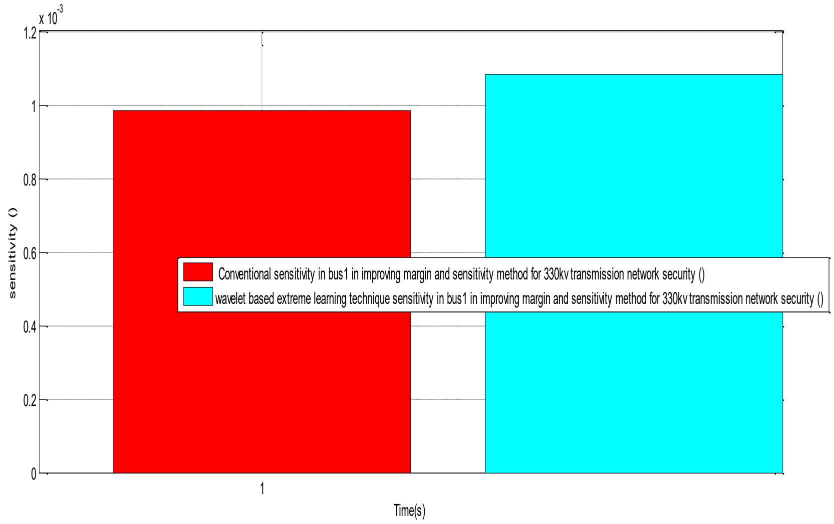

Fig 9: Bar Chart for comparisons of Conventional and Wavelet Sensitivity in 330kv Transmission Network Security

In figure 9 the conventional sensitivity is 0.000983 that caused transmission network failure. On the other hand, when wavelet is integrated in the system the sensitivity improved to 0.001081 thereby enhancing the stability of the transmission network.

Conclusion

This study has demonstrated the effectiveness of a wavelet-based extreme learning method (WELM) in bolstering the security of 330kV transmission networks. By integrating margin and sensitivity analyses with WELM, we have developed a robust framework for real-time fault detection and system monitoring. Future work will aim to further refine this method and explore its application to other components of the power system. The persistent power failures in the transmission network, which have hampered business activities due to low power margin and sensitivity, are mitigated by improving these parameters using the wavelet-based extreme learning technique. The process involves characterizing the 330kV transmission network, conducting load flow analysis to identify buses with low margin and sensitivity, developing a wavelet rule base to enhance these parameters, and training an artificial neural network (ANN) within this rule base. A SIMULINK model was designed to implement the wavelet-based technique, and an algorithm was developed to carry out this process. The approach was validated by comparing the network's performance with and without the WELM. The results showed that the conventional per-unit voltage of the weak bus 1 was 0.930, below the stability threshold of 0.95 to 1.05, leading to inconsistent power supply. Incorporating the wavelet-based extreme learning method increased the voltage to 1.023 per unit, achieving stability. Additionally, the conventional power margin of weak bus 1 was 58.85 MW, causing intermittent power supply. With the wavelet technique, the power margin increased to 64.73 MW, ensuring a constant power supply. The power margin improvement was 9.99%, and the sensitivity improved from 0.000983 to 0.001081, thereby enhancing the transmission network's stability and performance.

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