

Improving Margin and Sensitivity Method for 330kv Transmission Network Security Analysis Using Wavelet Based Extreme Learning Technique

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Abstract

The persistent power failure in the transmission network has jeopardized business and industrial activities as a result of low power margin and low sensitivity in the network. The power system operates stably at a certain loading level referred to as the “base case loading”. This work provides the process of surmounting this ugly development by the introduction of ‘improved margin and sensitivity method for 330kv transmission network security analysis using wavelet-based extreme learning technique’. The load flow of the characterized network was carried out to establish the buses that caused low margin and low sensitivity in the network, and a wavelet rule-based method was developed that will improve the margin and sensitivity of the network. An Artificial Neural Network (ANN) was trained in the developed wavelet rule base to improve the margin and sensitivity of network security analysis. A SIMULINK model for wavelet-based extreme learning technique was developed, and the algorithm that will implement the process was also developed. The implementation process worked smoothly with the designed SIMULINK model. The conventional per-unit voltage of weak buses does not attain the threshold voltage of 0.95 through 1.05 for stability, which was achieved by the new technique. The results show that the conventional per unit volts of weak bus 1 is 0.86, but was improved to 0.95pu volts. The power margin from 58.85MW to 64.73MW, which is about 9.99% improvement. The sensitivity is 0.000983, but was improved to 0.001086, which is about 9.96% improvement. The conventional sensitivity in bus 6 is 0.000987, which increased to 0.001086. And the conventional power margin was 42.31MW, increased to 46.54 MW, which is about 10% improvement. The incorporation of artificial intelligence (AI) in the system resulted to consistent power supply in the transmission system. The process was also validated and justified by calculating the percentage improvement in the margin and sensitivity of the network with and without the wavelet-based extreme learning technique, and it was observed that the system witnessed over ten percent (10%) improvement.

Keywords: Sensitivity, Transmission, Margin, Bus, Security, Network, Wavelet, Incorporation.

Introduction

Contingencies such as unexpected outages often contribute to voltage collapse and system blackouts (Anumaka, 2018; Okonkwo & Onoh 2022). These contingencies generally reduce

or even eliminate the voltage stability margin. To maintain security against voltage collapse, it is desirable to estimate the effect of contingencies on the voltage stability and MW margin (Duruibe & Ojukwu, 2019). To Onojo, Ononiwu, & Okozi, (2017), remedial action can be taken to increase the margin so that likely contingencies do not cause blackout. The power system operates stably at a certain loading level referred to as the "base case loading". The electric power consumption is increasing day by day and thereby increasing the power system complexity, making the system operate almost within instability range (Izuegbunam, Duruibe & Ojukwu, 2019). When contingencies occur in any bus, there will be a changing the loading margin and voltage drop in a specified bus. By calculating Maximum Loading Point (MLP) and Mega Watt Margin (MWM), we can estimate the critical contingency and to take remedial action to avoid the voltage instability. Under normal conditions the system does not experience any voltage stability problem and all components work correctly in the system. The system can operate at Maximum Loading Point (MLP) and so it corresponds to Maximum MW Margin (MMWM). Hence, to analyze how much power system is utilized safely, it needs to simulate possible contingencies of power system and network performance to be considered for each contingency (Chan et al 2019). From the literature, voltage stability and contingencies ranking are necessary aspects of voltage security. Ranking of all possible contingencies based on their impact on the system voltage profile will help the operators in choosing the most suitable remedial actions before the system moves toward voltage collapse. The possible contingencies with ranking according to line Fast Voltage Stability Index (FVSI) indicator are carried out (Musirin et al, 2002; Akinloye, Oshevire, & Epemu, 2016; Azman et al, 2020). The methods of ranking the possible contingency based load shedding are given in (Adebayo, 2013; Ogunjuyigbe & Ayodele 2015; Akinloye et al, 2018).

The artificial intelligence, possible contingency ranking is done based on Neural Networks ((Jain et al 2003), (Fuzzy Logic (Mori, et al,200)) and Particle Swarm Optimization (PSO) (Abdelaziz, 2009), (Saravanan et al, 2007), Continuation method Song et al, (2006). In this work, Continuous Power Flow (CPF) is applied in calculating the MLP and its corresponding to MWM, decreased percentage in each contingency. Then we can rank all the possible contingencies based on the severity of their effect on voltage stability.

In power system, load expansions are causes of the voltage drop and the reduction of efficiency. Power factor improvement is very necessary, and installed capacitor banks is needed for the job. Capacitor banks are used extensively in power system for power factor improvement or for compensation of reactive power demand of large commercial and industrial load. The optimal design of the power factor improvement in the power system is important from a technical point of view. The optimal capacitor placement is to determine the location of the capacitor banks to be installed on the power system that will maximize the system power factor, reduce total system generation cost and reduce the total system losses, while the power system can serve the demand of loads.

Optimal power flow is used to determine the optimal system operating point at the lowest total generation cost while enforcing a variety of operational constraints such as the limit

of bus voltages, line flows, real power generator and reactive power generator of all busses (Bashar et al, 2016). The OPF problem has a long history in power system research. A variety of numerical techniques developed for this problem are as non-linear programming method, quadratic programming method, linear programming method, interior point method and Lagrange Newton method

The Lagrange Newton method (Gupta et al, 2010, (Gyugyi, 2000) is employed in this paper because sensitivity analysis needs the matrix of the second order derivatives of Lagrange function from OPF problem to determine the change of the objective function with respect to the change of injected reactive power. After adding the capacitor banks to the power system being equivalent to reduce reactive loads, the optimal system operating point is changed. The sensitivity analysis is used to evaluate the optimal location of the capacitor banks by determining the sensitivity of the optimal system operating point to a change in reactive load at each bus in which the capacitor bank is added. The objective of optimal capacitor placement is to maximize the system power factor so that the optimal capacitor placement is the bus where yields the highest system power factor and reduces the total system losses while reducing the total system generation cost (Onohaebi & Igbinovia, 2018). The sensitivity method is described in details in the next section, and applied to 5bus and 9-bus test systems. The results from the test systems by sensitivity analysis give the same incremental system power factor, and thus the same optimal locations as the ones from the differencing method

Some parameters in a system can be set or controlled while others such as loads are mostly uncontrolled. The uncontrolled parameters can vary with time and affects the behavior of the power system (Rajiv, Varma, Noroozian, & Taylor, 2018). The difference between the parameter values corresponding to an event and the current parameters define the margin to the event. For instance, if the increase in flow on a line is caused by increasing loads, one might measure the distance to a line tripping by a suitable norm of the vector difference in loads, a loading margin. Depending on the application, security margins can be measured in parameter space with respect to load levels, load model parameter, import levels, temperature, or time (Zhang, 2016) When the security margin measures the distance to an event that causes the system to become unstable, it is called a stability margin.

In some instances, it may be practical to measure the security margin in with a state variable or a function of state. For example, the amount of additional real power flow on a line that would cause overload is an easily understood measure of closeness to overload of that line. Examples of margins measured in state space are increments in line flows, generator VAR outputs, and voltage levels (Laszlo, Schauder & Kalyan, 2017; Izuegbunam, Duruibe & Ojukwu, 2019). The system equilibrium, and thus margins to events, is affected by both controllable and uncontrollable parameters. The sensitivity of margins with respect to uncontrollable parameters quantifies the effects of different assumptions, forecasts, and measured data. System operation also requires knowledge of how the controllable parameters can be adjusted to keep the system secure as the uncontrollable parameters change. One way of quantifying the effectiveness of controls is by computing the sensitivity

of the security margin with respect to the control parameter (Kumar et al. 2007; Umar & Nagaraju, 2017)

Consider the case of a line approaching overload. By computing the sensitivity of the line flow with respect to different loading patterns, one can estimate the worst case loading pattern the one that increases the line flow most rapidly. The loading margin for this load pattern can then be computed by solving for a continuation of equilibrium as the loading level is gradually increased. The continuation neglects the transients and dynamics of the power system (Akinloye, 2016). However, the locus of equilibrium approximates the trajectory of the system state for sufficiently stable dynamics and slowly varying load level. Once the loading level at which the line reaches overload is located and hence the loading margin found, the sensitivity of the loading margin with respect to any parameters can be calculated. For example, computing the sensitivity of the margin with respect to the import power set points can be used to assess the possibility of avoiding the overload by changing the imports. There are several ways to improve the stability margin of a power system, depending on type and location of the fault, and the characteristics of the system. For instance, increasing generation or reducing load can reduce power transfer and stress on transmission lines.

Additionally, adding or adjusting reactive power compensation devices, such as capacitors or FACTS, can improve voltage profile and power angle stability (Bashar & Chin, 2016; Bashar & Chin, 2016). Other methods include enhancing the speed and coordination of the protection system to reduce ACT, implementing special protection schemes such as load shedding or islanding to isolate or mitigate fault impact, and applying advanced control techniques like adaptive protection or artificial intelligence to monitor and optimize system stability in real time.

Many system models have been designed for online computation of voltage collapse sensitivity indices. Margin sensitivity is useful in determining the effectiveness of different parameters for enhancing system loading margin (Lasantha, 2020) The stochastic response surface method (SRS) is an effective method, which uses statistics and probability distributions concept to estimate transmission reliability margin (TRM). The probability of normal operation of electric grid to satisfy end users' power demand at any time is known as power system reliability. It usually varies with time and characterize the ability of the electrical system to supply customers with adequate electricity. To affirm the reliability of any designed system, it must be able to perform decently under the desired conditions over a specified period. The definition of reliability has four based parts; probability, adequate performance, time, and operating conditions. Moreover, reliability refers to the probability of a system/device performing its purpose adequately for the period intended under the operating conditions encountered (Abido, 2002). Reliability ends when the system stops to perform its intended function, and then unreliability occurs. Under specified system conditions, how reliably power can be transferred from one area to another through all transmission lines of interconnected electric system is known as transfer capability. The whole concept of reliability is based on probabilistic characterization. Reliable operation of

large scale electric power networks requires the system voltages and currents within designed limit. Operation beyond those limits can lead to equipment failures and blackouts. Security margin measure the amount by which system load or power transfers can change before a security violation such as an overloaded transmission line, is encountered. This work shows how to efficiently compute security margins defined by limiting events and instability, and sensitivity of those margins with respect to assumptions, system parameters, operating policy, and transaction. Security margins to voltage collapse blackouts, oscillatory, instability, generator limits, voltage constraints and line overloads are considered. The usefulness of computing the sensitivities of this margins with respect to inter area transfers, loading parameters generator dispatch, transmission parameters and VAR support is established for networks as large as 1,500 buses. The sensitivity formulae presented applied to a range of power system models. Conventional sensitivity formulae such as line distribution factors, participation factors and penalty factors are shown to be special case of the general sensitivity formulae derived. The sensitivity formulae readily accommodate wavelet extreme learning techniques (Ezeruigbo et al, 2015). Margin and sensitivity methods are shown to work effectively to avoid voltage collapse blackout caused by either saddle node bilocation equilibrium or immediate instability due to generator reactive power limits. Extremely fast contingency analysis for voltage collapse can be implemented with margin sensitivity based rankings. Inter area transfer can be limited by voltage limit, line limit or voltage stability. The sensitivity formulae presented in this work applied to security margin defend by any limit criteria. A method to compute transfer margins by directly locating intermediate events, reduce the total number of load flow iterations required by each margin computation and sensitivity information are minimal with additional cost. Estimates of the effect of simultaneous transfers on the transfer margins agree well with the exact computations for a network model derived from a portion of the U.S. grid. The accuracy of the estimate over a useful range of condition and the ease of obtaining suggest that the sensitivity computation will be of a practical value.

Voltage stability is a fundamental component of dynamic security assessment and it emerged through major concern for power transfer. Voltage stability is usually expressed in terms of stability margin limit for loading and power transfer. Voltage stability is usually expressed in terms of stability margin.

Stability margin is the difference between the critical clearing time (CCT) and the actual clearing time (ACT) of a fault in a power system. Critical clearing time (CCT) is the maximum time that a fault can persist before causing instability, while actual clearing time (ACT) is the actual time that the fault is cleared by the protection system. The larger the stability margin, the more resilient the power system is to disturbances (Dikki, 2014) Stability margin can be expressed as a percentage of critical clearing time (CCT), or as a time margin in seconds. The stability margin of a measure of how far the system can withstand disturbances before losing its synchronism and stability. It is a crucial parameter for the

operation and planning of a power system, as it affects the security, reliability, and efficiency of the grid.

A power system can be utilized in a safe manner when the occurrence of each possible contingency and system does not exit from normal system security. Power system works in abnormal manner when variables exit from their allowed limit. Each event that occurs in the power system would change the configuration of network that itself results in contraction of λ -V curve and there is a decrease in MLP and its corresponding change in MWM. Hence, under normal conditions when systems do not experience a contingency and all components work correctly, the system can have Maximum Loading Point (MLP) and Maximum MW Margin (MMWM). In a power system, we encounter many contingencies that may result in overload in some of the lines and bus voltages deviation from their allowed limit so that the position of the weakest bus may change. The system may be operating at a stable equilibrium point but a contingency at maximum loading point which can affect the overall reliability of the system (Gyugyi, 2000).

Reliable operation of large scale electric power networks requires that system voltages and currents within design limits. Operation beyond those limits can lead to equipment failures and blackouts. Security margins measure the amount by which system loads or power transfers can change before a security violation, such as an overloaded transmission line, is encountered. System power margin reflects the excess signal level, present at the input of the receiver that is available to compensate for; (a) the effects of component aging in the transmitter, receiver, or physical transmission medium, and (b) deterioration in propagation conditions, Synonym system power margin.

In recent years, computer technology has witnessed rapid evolution such as the machine learning technology. The concept machine learning (ML) comes from the recognition of the theory that computers can learn to perform specific function without being programmed. Extreme Learning (EL) is a branch of artificial intelligence that allows a computer to learn and produce reliable decisions and results using a set of data. Based on this, a rapid learning algorithm based on single feed-forward neural networks (SFFNNs) named extreme learning machine (ELM) was developed (Ezeruigboa, et al, 2015). It is different from the traditional learning method such as back propagation (BP) algorithm. It is a non-interactive approach with minimal human intervention, apart from extreme learning machine technique, deep neural network, which is an artificial neural network (ANN) algorithm having more than one hidden layer between its input and outputs, performs well in many machine learning fields. Combining neural networks and wavelet theory has led to the introduction of Wavelet Neural Network (WNN) method which appears to be an effective prediction algorithm in many domains. The original goal of the WNN approach was to approximate signals using small wave called wavelet. It gives a good generalization performance in handling large dimensional classification problems because it is based on both time and frequency properties. In the beginning, it was applied in image classification, and then used in many other fields, such as video segmentation, speech recognition, and compression (Braide & Diema, 2018) Feed-forward neural network (FFNN) have being used in many research works

related to the machine learning field and have gained wide approval. Despite these advantages, the FFNN has lately been proven to be slower than required (Ghasemi et al, 2007). Consequently, it has received substantial criticism for some of its applications. ELM was introduced as a simple and fast solution to this problem. Out of numerous machine learning techniques, Support Vector Machine (SVMs) and Neural Network have played important roles. Nevertheless, both methods face some challenges like the necessity of human intervention, the slow learning and lack of computational scalability. Emerging technologies, such as Extreme Learning Machine (ELM), Deep Learning (DL) and Wavelet Neural Network (WNN) have overcome some challenges faced by other methods. Compared with other algorithms, extreme learning machine (ELM), reaches satisfactory generalization performance with minimal human intervention (Hingorani, 1991). Furthermore, the learning speed of ELM is exceptionally fast compared to other traditional methods. However, previous works demonstrate the sensitivity of the ELM algorithm to the choice of the activation function type (Ayodele, et al, 2016). Aside that, most researchers demonstrated the reliability and stability of wavelet neural networks (Rafiqul et al, 2012) in performing the classification task. The capacity of WNN in the decomposition in both time and frequency domains proves their importance. For these reasons, it is important to integrate wavelet neural networks with extreme learning machine. The proposed technique employs the use of auto encoder to solve the problem of stability in Extreme Learning Machine. Wavelet Extreme Learning Machine Auto-Encoder (WELMAE), was used to solve stability problem by merging the wavelet neural networks as a composite activation function. Thus, we propose to integrate wavelet neural networks with extreme learning machine.

Statement of the Problem

The intermittent power supply observed in the transmission network is as a result of low power margin and low sensitivity in the network. The core cause of this major power issue seems to be because of not running the load flow to identify the faulty buses, with their per unit voltage (Puv) not within the stability range of 0.95 through 1.05, which causes low margin and low sensitivity in the network. Despite huge government investment in power sector, stable power supply from the transmission network remains a mirage, causing untold hardship to the entire electricity consumers in the country. This inconsistent power supply in the transmission network have caused terrible havocs to all the sectors of the economy of the country by halting down operations and processes for reasonable length of time. Some industries and establishments that solely depend on power supply to run their daily production activities have gone moribund with little or no hope of resuscitation. This ugly trend if unchecked have the capacity of grounding the economic growth and development of the country. Hence, the need for the introduction of 'improving margin and sensitivity method for 330kv transmission network security analysis using wavelet extreme learning technique to eradicate the constant power failure observed in the country. However, lack of adequate knowledge of the use of Artificial Intelligence to monitor the

network and maintain good margin and sensitivity in the network appears to be hindering the new innovations. It is on this basis that this study was embarked on to be able to contribute in the ongoing debate about eradicating epileptic power supply in Nigeria by achieving the under listed objectives.

Research Objectives

1. To characterize 330KV transmission network.
2. To run the load flow of the characterized network to establish the buses that caused low margin and low sensitivity in the network.
3. To develop a wavelet rule base that will improve the margin and sensitivity of 330KV transmission network.
4. To train ANN in the developed wavelet rule base to improve the margin and sensitivity method of 330KV transmission network security.
5. To design a SIMULINK model for wavelet based extreme learning technique
6. To develop an algorithm that will implement 3, 4 and 5.
7. To design a SIMULINK model for improving margin and sensitivity method for 330kv transmission network security using wavelet based extreme learning technique.
8. To validate and justify the percentage improvement in the margin and sensitivity of the network with and without wavelet based extreme learning technique.

Review of Relevant Literature

Basically, the bulk transportation of electrical energy from a generating location, such as a power station or power plant, to an electrical substation, where voltage is changed and transmitted to consumers or other substations, is known as electrical power transmission. In the process of this transmission, several categories of faults occur along the transmission line and these affect electricity deliveries in many ways. Any aberrant electric current in an electric power system is referred to as a fault or fault current. A short circuit, for instance, occurs when a live wire touches a neutral or ground wire.

Transmission line stability

This is the ability of the power system to maintain synchronous operation and return to equilibrium after a disturbance. It is important for preventing widespread power outages. Transmission line stability includes; Steady-state stability, transient stability and voltage stability. Steady-state stability: This type of stability focuses on the ability of the system to maintain stable voltage and power flow under normal operating conditions. Transient stability: This type of stability assesses the ability of the system to stay in synchronism and operates normally after large, sudden disturbances like faults. Voltage stability: This is the ability of the power system to maintain acceptable voltage levels under the stress of power flows and reactive power imbalances, preventing voltage collapse.

Methods of enhancing stability

Transient stability in the transmission network can be improved through the following ways;

Series Compensation: Inserting series capacitors in the line reduces the total line reactance, increasing the minimum power that can be transferred and improving stability.

Shunt compensation: Shunt capacitors are used to supply reactive power to the load side, which reduces voltage drop, compensates for inductive loads, and helps improve power factor and stability.

System design and protection: Careful design of transmission towers, their fundamentals in stable geological area, and the use of appropriate structural analysis for wind loads are essential for maintaining mechanical stability.

Power flow studies

Power flow otherwise known as load flow is an important part of power system analysis. They are necessary for planning, economic scheduling, and control of an existing system as well as future expansion considerations. The task consists majorly of the determination of the magnitude and phase angle of voltages at each bus and the active and reactive power flow in each line. The three parameters in load flow includes; voltage magnitude $|V|$, phase angle, real power P . and reactive power Q . The system buses are generally classified into three types.

Slack bus: The slack bus is taken as the reference where the magnitude and phase angle of the voltage are specified. This bus makes up the difference between the scheduled load and generated power that are caused by the losses in the network.

Load buses: At the load buses the active and reactive powers are specified. The magnitude and the phase angle of the bus voltage are unknown. These buses are called P-Q buses.

Regulated buses: These buses are also known as generator buses or voltage-controlled buses. At these buses, the real power and voltage magnitude are specified. The phase angles of the voltages and the reactive power are to be determined. The limits on the value of the reactive power are also specified. These buses are called P-V buses.

The common causes of faults in transmission lines include:

- Aircraft and cars hitting lines and structures
- Birds and animals
- Contaminated insulators
- Ice and snow loading
- Lightning
- Partial discharges (corona) not controlled
- Punctured or broken insulators
- Trees
- Wind
- Others

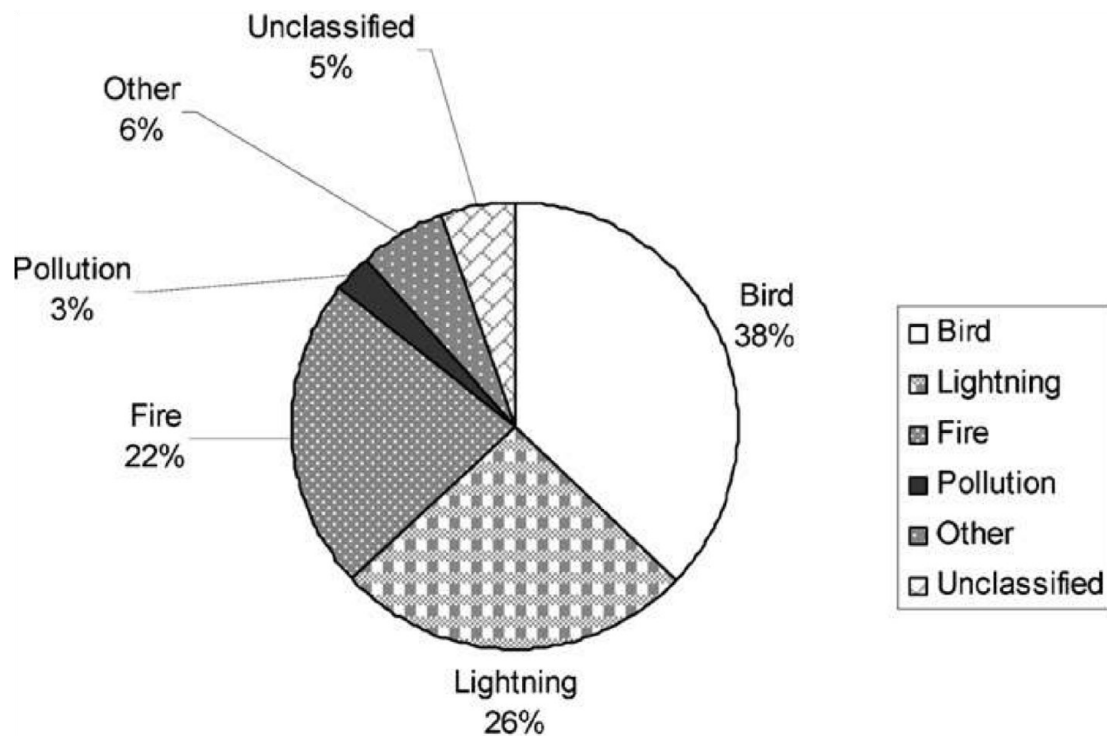


Figure 2.1: Categorization of Faults in the Transmission Line

Wavelet Transform Theory

A wavelet is such a function $\psi \in L^2(\mathbb{R})$ with a zero average, Wavelet transform is the decomposition of signals over dilated and translated wavelets. Stéphane Mallat gives this definition as shown in equation (1), (Mallat, 2009).

$$\int_{-\infty}^{+\infty} \psi(t) dt = 0 \quad (2.01)$$

Characteristically, the wavelet function having a zero average is also proved to be normalized that is $\|\psi\| = 1$ and its center lies in the region of $t = 0$. The spatial region where this wavelet function is defined contain various points which (Mallat, 2009) calls time-frequency atoms. For one instance if the wavelet function is scaled by some factor s and moved/translated along its axis by some units, u then D would define the sets of time-frequency atoms that would reside in this region in equation

(2) as:

$$D = \left\{ \psi_{u,s}(t) = \frac{1}{\sqrt{s}} \psi\left(\frac{t-u}{s}\right) \right\}_{u \in \mathbb{R}, s \in \mathbb{R}^+} \quad (2.02)$$

Just like already defined these atoms are also normalized i.e. $(\|\psi_{u,s}\| = 1)$.

To add a proper definition Wavelet transform convolves a signal with such wavelet function and the signal is thus decomposed into different frequency and time-period characteristics. (Zuoxun & Liqiang, 2020)

For some function, f defined such that $f \in L^2(\mathbb{R})$ exists on the two dimensional space at time u and scaled to s : we write wavelet transform of f with (Mallat, 2009) definition in equation (3) as:

$$(u, s) = \langle f, \psi_{u,s} \rangle = \int_{-\infty}^{+\infty} f(t) \frac{1}{\sqrt{s}} \psi^* \left(\frac{t-u}{s} \right) dt \quad (2.03)$$

Equation (3) can be rewritten as shown in equation (4) as:

$$W_f(u, s) = \int_{-\infty}^{+\infty} f(t) \frac{1}{\sqrt{s}} \psi^* \left(\frac{t-u}{s} \right) dt = f \star \bar{\psi}_s(t) \quad (2.04)$$

The above shows that this wavelet transform of f is the convolution product of f and the wavelet function $\bar{\psi}(t)$ which is defined in equation (2.05) as:

$$\bar{\psi}_s(t) = \frac{1}{\sqrt{s}} \psi^* \left(\frac{-t}{s} \right) \quad (2.05)$$

The Fourier transform of $\bar{\psi}(t)$ reveals composite frequency arrangement of this function since (Mallat, 2009) proved that this convolution acted as though the function implemented some expanded band-pass filters.

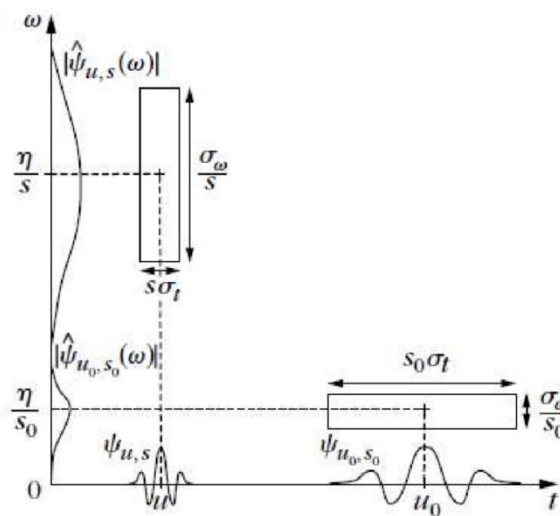


Figure 2.2: Heisenberg boxes of two wavelets. Smaller scales decrease the time spread but increase the frequency support, which is shifted toward higher frequencies

Sources: Adapted with modification from Mallat (2019).

Discrete wavelets

The definition of discrete wavelets extends that already given for the continuous wavelet, discrete wavelets allow for sampling at intervals to represent the time-frequency components. (Mallat, 2009) shows that for some $f(t)$ which is a continuous time signal defined over the closed interval of $[0, 1]$ then by passing f through a low pass filter and sampling at the interval N^{-1} then for the resulting discretized signal $f[n]$, we can only calculate its discrete wavelet transform in the range from N^{-1} to 1, and by discretizing $\psi_{a,b}(t)$ the convolution is expressed in equation as:

$$\psi_{j,k}(t) = a_0^{-(j/2)} \psi \left(\frac{t - ka_0^j b_0}{a_0^j} \right) = a_0^{-(j/2)} \psi(a_0^{-j} t - kb_0) \quad (2.06)$$

And the discretized wavelet transform is:

$$C_{j,k} = \langle f, \psi_{j,k} \rangle = a_0^{-(j/2)} \int_{-\infty}^{+\infty} f(t) \bar{\psi}(a_0^{-j} t - kb_0) dt \quad (2.07)$$

As shown in Mallat (2009), Zuoxun and Liqiang, (2013) that in the transformed signal, the coefficients C_j , of this transform can in some cases characterize (t) completely.

Wavelet decomposition algorithm

The decomposition algorithm applied expressed the coefficients and scale function, in decomposition the spectrum is limited.

To represent that the decomposed function would consist the wavelets decomposition coefficients, we have that:

$$(t) = \sum_n C_{j+1}, \varphi_{j+1},(t) \quad (2.08)$$

and $C_{j+1,n}$ and $\varphi_{j+1,l}(t)$ are the scale functions of scale space and a function $\langle f, \varphi_{j+1,n} \rangle$.

This formula is rewritten to show the high and low frequency components of the function:

$$(t) = \sum_n C_j, \varphi_j,(t) + \sum_n d_{j,k} \psi_{j,k}(t) \quad (2.09)$$

The left half of the formula above comprises the low-frequency component of (t) , otherwise the approximate part of $f(t)$, and the right half comprises the high-frequency component otherwise the detail part of $f(t)$ (Zuoxun & Liqiang, 2020). This presents the coefficients C_j , and d_j , are the approximate and detail coefficient terms. They can be obtained as follows:

$$C_j, = \langle f, \varphi_j, \rangle = \sum_n c_{j+1,n} \bar{h}_{j-2k} \quad (2.10)$$

$$d_j, = \langle f, \psi_j, \rangle = \sum_n c_{j+1,n} \bar{g}_{j-2k} \quad (2.11)$$

The above formula shows that in the space V_{j+1} , next approximate and detail coefficient can be obtained from the current coefficients. The process is represented in the figure below

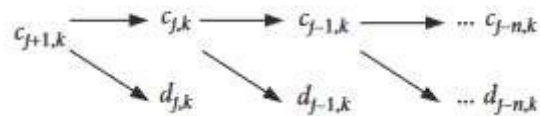


Figure 2.3: Decomposition Process

Wavelet reconstruction algorithm

The reconstruction algorithm reverses this process of deconstructing a wavelet function. Zuoxun and Liqiang (2020) referred to the Mallat reconstruction algorithm in this manner. Introducing these obtained expressions for eqn (2.10) and eqn (2.11) into eqn (2.12), $f(t)$ can be obtained as:

$$\begin{aligned} (t) &= \sum_k c_j, (\sum_l h_{l-2k} \varphi_{j+1},(t)) + \sum_k d_{j,k} (\sum_l g_{l-2k} \varphi_{j+1},l(t)) \\ &= \sum (\sum_k c_{j,k} h_{l-2k} + \sum_k d_{j,k} g_{l-2k}) \varphi_{j+1},l(t) \end{aligned} \quad (2.12)$$

Similarly, Mallat (2009), Zuoxun and Liqiang, (2020) has also presented this algorithm and reconstructs the next coefficients c_j , and d_j , from the current ones.

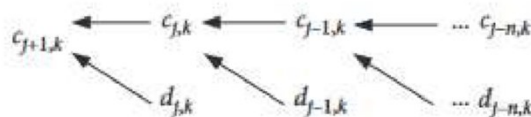


Fig. 2.4 Reconstruction Process

The figure above illustrates this reconstruction process.

Wavelet and ANN technique

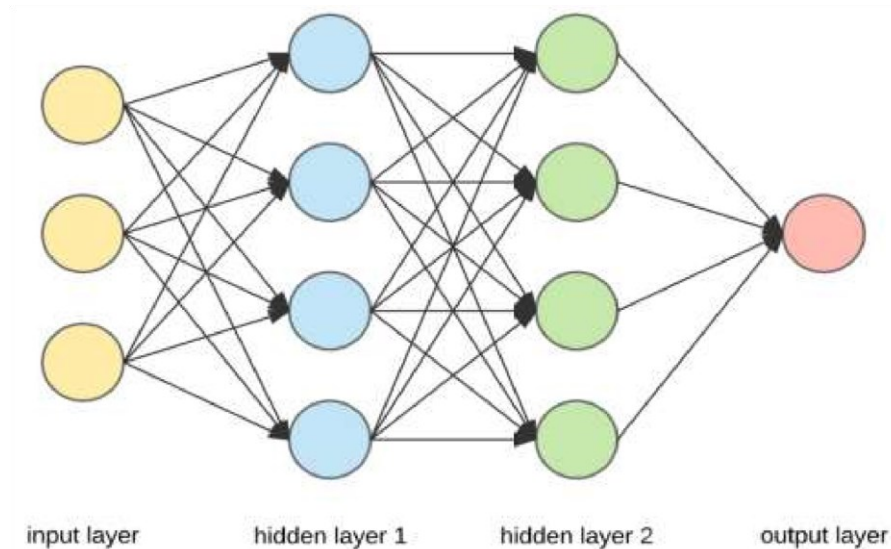


Fig. 2.5 Artificial Neural Network (ANN)

Artificial Neural Network (ANN) has come to mean any architecture that has massively parallel interconnections of simple processors. Theoretically, ANN can be considered as conveniently a parameterized class of non-linear maps. Many authors have proven that a multi-layer neural network is capable of representing any non-linear continuous functions to any degree of required accuracy so far the network is well trained. This development has generated wide attention in control applications. This, inherent parallel and distributed architecture of ANN can be successfully employed in ultra-capacitor frequency stability enhancement of the Nigerian 330KV transmission networks.

Steps involved in development of ANN are done in two phases; the training phase and the testing phase.

(1) The training phase

In this phase, the ANN tries to memorize the pattern of leaning set. This is made up of the following modules -

- i. Selection of neuron characteristics: Neurons can be characterized by two operations, namely aggregation and activation function. Nonlinear filter also known as activation function can be characterized by several functions which include the following; Hard limit (hardlim), symmetrical hard limit (hardlims), linear (purelin), saturating linear (sat lins), log sigmoid (log sig), hyperbolic tangent sigmoid (tan sig), positive linear(poslin), and competitive (compet) functions. Selection of the function is problem dependent. For instance, the logarithmic

activation is used when the upper limit is unbounded while the radial basis function (RBF) is used for problems having complex boundaries.

- ii. Selection of topology: Topology of ANN deals with the number of neurons in each layer and their interconnections. Too few hidden neurons hinder the learning process, while too many occasionally degrades the generalization capability. There are no-clear-cut or absolute guidelines available in the literature for deciding the topology of ANN. One rough guideline for choosing the number of hidden neurons is the geometric pyramid rule.
- iii. Error minimization process: When ANNS are trained, the weights of the links are charged / adjusted so as to achieve minimum error. During this process, a part of the entire data set is used as training set, and the error is minimized on this set. Calculations for error maybe done using various functions. The most commonly used being the Root Mean Square (RMS) function and is given by error = $\frac{1}{2}(\sum [actual - predicted]^k) \dots \dots 2.21$

Where K is order of norm.

- i. Selection of training pattern and preprocessing.

Selection of data is very critical for building ANN. Although preprocessing is not mandatory, it definitely improves the performance of the network and reduces the learning time.

- ii. Stopping criteria for training

The process of adjusting weights of an ANN is repeated until the termination condition is met. The training process may be terminated if any one of these conditions is met:

1. The error goes below a specific value
2. The magnitude of gradient reaches below a certain value 3) Specific number of iteration is complete.

Materials and Method

Hardware:

- Laptop: This is a personal computer unit for performing multiple numerical and data applications.

Software:

- MATLAB SIMULINK: A "high-performance language" used in technical and engineering computing.
- Microsoft word: This is where all the work done is written for perusal.

Simulation Software:

- MATLAB SIMULINK: A "high-performance language" used in technical and engineering computing.
- Microsoft word: This is where all the work done is written for perusal.

Design Method

EXPERIMENTAL SET UP

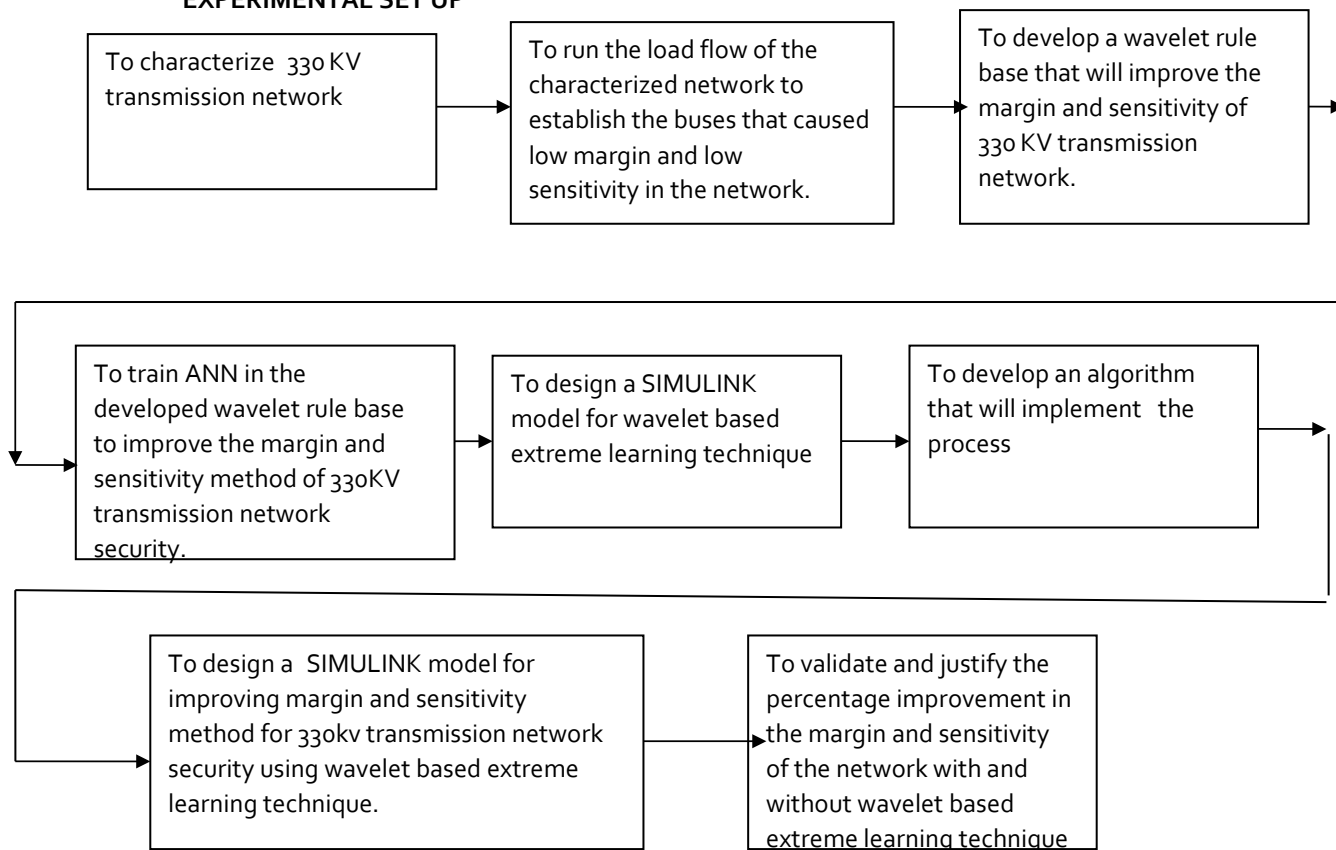


Fig. 3.1 The block diagram of the work

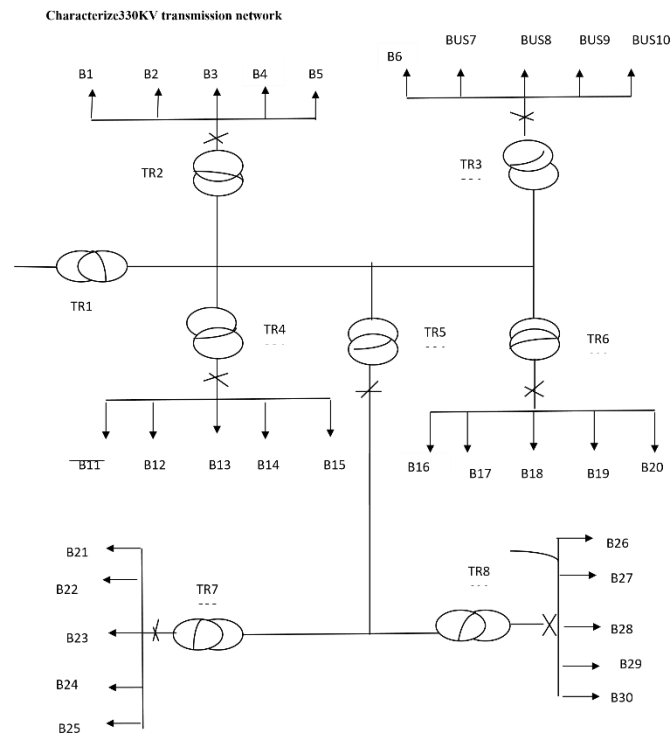


Fig 3.2 Line diagram for improving margin and sensitivity method for 330kv transmission network security.

A wavelet fuzzy inference system that will improve the margin and sensitivity of 330kv transmission network was developed. This was done at the Fuzzy Tool Box using Fuzzy editor. In a similar way, a wavelet rule base that will improve the margin and sensitivity of 330kv transmission network security was developed as shown below.

Table 3.1 Wavelet rule base that will improve the margin and sensitivity of 330kv transmission network security.

1	IF VOLTAGE IS NOT WITHIN PER UNIT VOLTS OF 0.95 THROUGH 1.05 IMPROVE	AND POWER MARGIN 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

ANN was trained in the developed wavelet rule base, ten (10) times to enable it work like human brain for the purpose of improving the margin and sensitivity of the network. Also, a SIMULINK model for wavelet based extreme learning technique designed using Matlab software, followed by the development of an algorithm that will implement the above steps as shown in the flow chart.

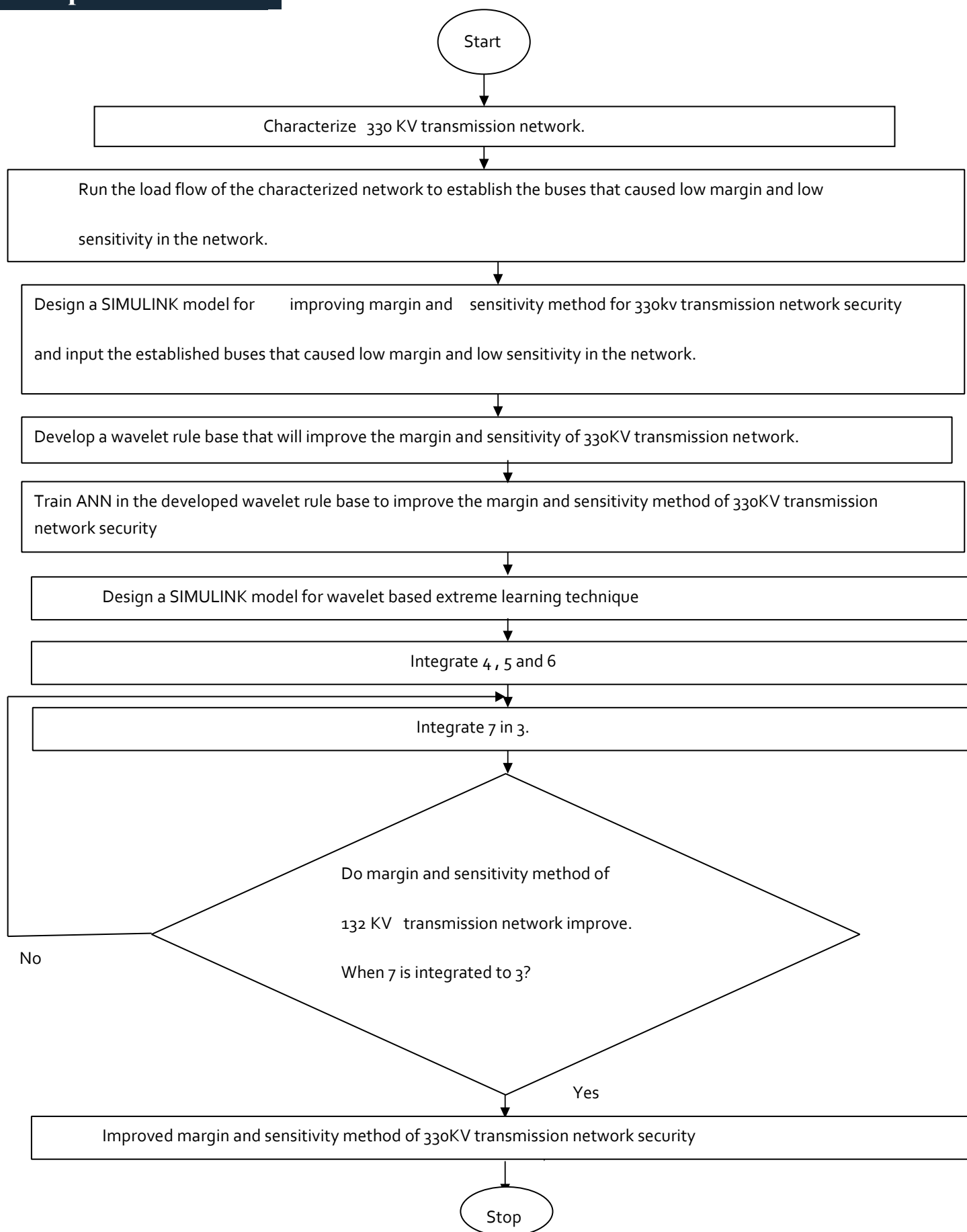


Fig. 3.3 The flow chart of the technique

Results and Analysis

Comparison of the results

Table 4.1 comparisons of Conventional and wavelet based extreme learning technique voltage in bus1 in improving margin and sensitivity method for 330kv transmission network security

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	0.86	0.95
2	0.86	0.95
3	0.86	0.95
4	0.86	0.95
10	0.86	0.95

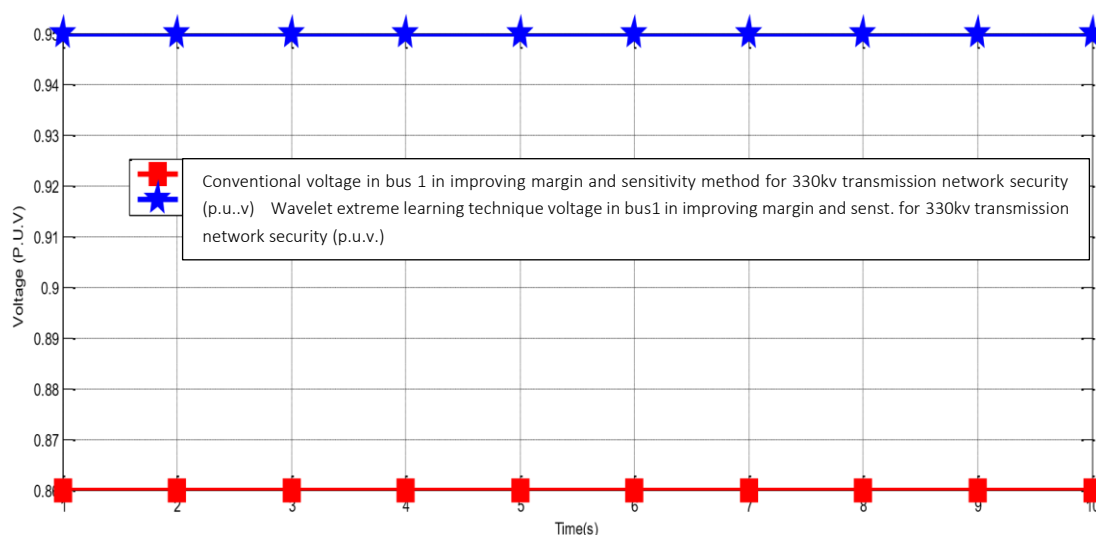


Figure 4.1: Comparisons of Conventional and wavelet based extreme learning technique voltage in bus1 in improving margin and sensitivity method for 330KV transmission network security

Figure 4.1 shows that the conventional per unit volts of weak bus 1 is 0.86 this does not attain the threshold of 0.95 through 1.05 for stability, this constitutes instability in the power system network. Meanwhile, when wavelet based extreme learning technique was incorporated in the system the voltage is boosted to attain the stability threshold with 0.95 per unit volts thereby enhancing consistent power supply in the transmission network.

Table 4.2 comparisons of 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

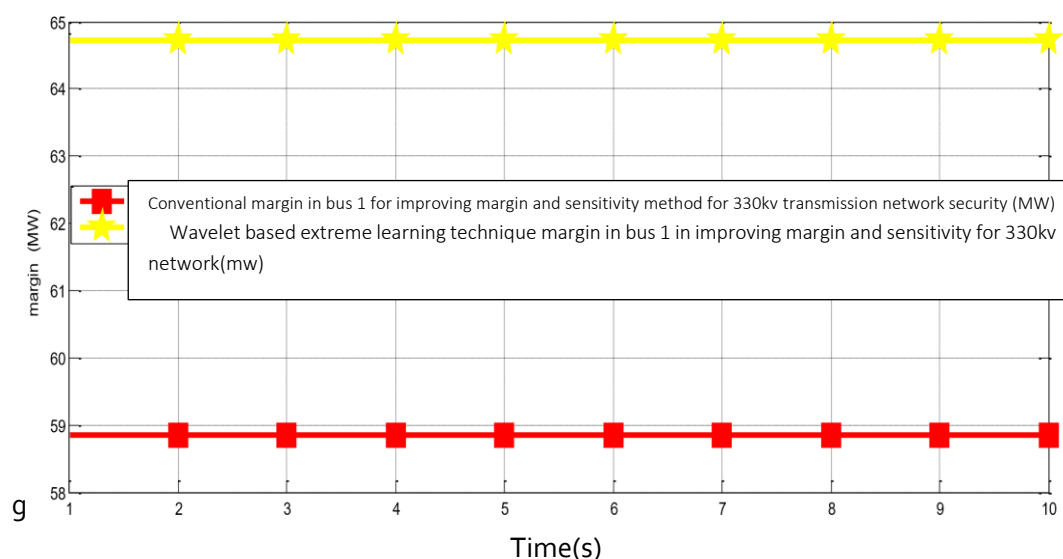


Figure 4.2 comparisons of Conventional and wavelet based extreme learning technique for margin in bus1 in improving margin and sensitivity method for 330kv transmission network security

The conventional power margin in weak bus 1 is 58.85MW causing intermittent power supply in the transmission network. On the other hand, when wavelet technique is integrated in the system it increased to 64.73MW thereby enhancing the constant power supply in the transmission network. The percentage improvement in the power margin when wavelet is incorporated in the system is 9.99%.

Table 4.3 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

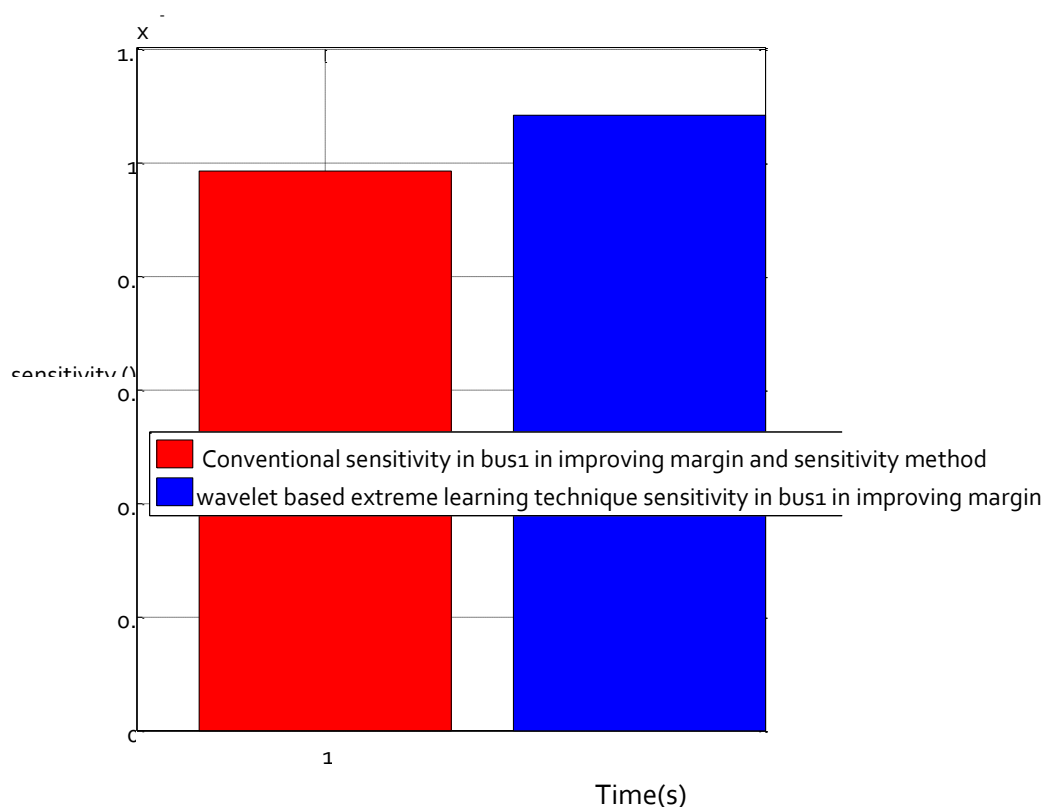


Figure 4.3 bar chart for comparisons of Conventional and wavelet based extreme learning technique for sensitivity in bus1 in improving margin and sensitivity method for 330kv transmission network security 0.001081.

In figure 4.3 the conventional weak bus 1 power sensitivity is 0.000983 while when wavelet is integrated in the system it improved to the percentage improvement in the power sensitivity when wavelet is incorporated in the system is 9.96%.

Table 4.4 comparisons of Conventional and wavelet based extreme learning technique voltage in bus 2 in improving margin and sensitivity method for 330kv transmission network security

Time(s)	Conventional voltage in bus 2 in improving margin and sensitivity method for 330kv transmission network security (P.U.V)	wavelet based extreme learning technique voltage in bus 2 in improving margin and sensitivity method for 330kv transmission network security (P.U.V)
1	0.867	0.9537
2	0.867	0.9537
3	0.867	0.9537
4	0.867	0.9537
10	0.867	0.9537

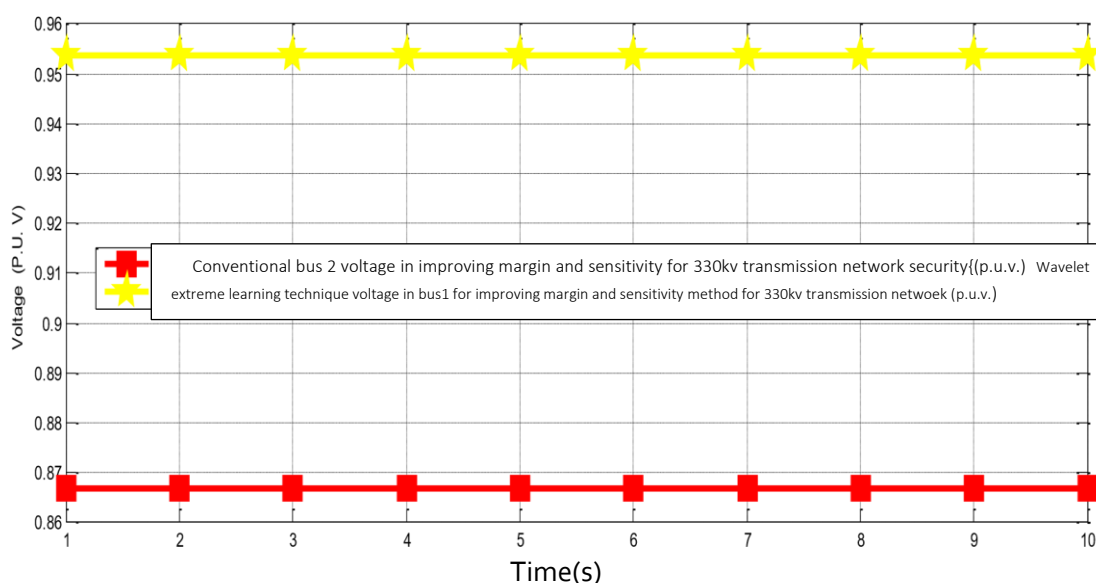


Figure 4.4 comparisons of Conventional and wavelet based extreme learning technique voltage in bus 2 in improving margin and sensitivity method for 330kv transmission network security

The conventional per unit volt of weak bus 2 is 0.867 which cause irregular power supply in the transmission network. On the other hand, when wavelet is incorporated in the system, it is 0.9537 per unit volts meeting the thresh hold of 0.95 through 1.05 thereby improving the performance of the network. the percentage improvement in the voltage when wavelet is introduced in the system is 10.03%.

Table 4.5 comparisons of Conventional and wavelet based extreme learning technique for Margin in bus2 in improving margin and sensitivity method for 330kv transmission network security

Time(s)	Conventional margin in bus2 in improving margin and sensitivity method for 330kv transmission network security (MW)	wavelet based extreme learning technique margin in bus2 in improving margin and sensitivity method for 330kv transmission network security (MW)
1	44.61	49.07
2	44.61	49.07
3	44.61	49.07
4	44.61	49.07
10	44.61	49.07

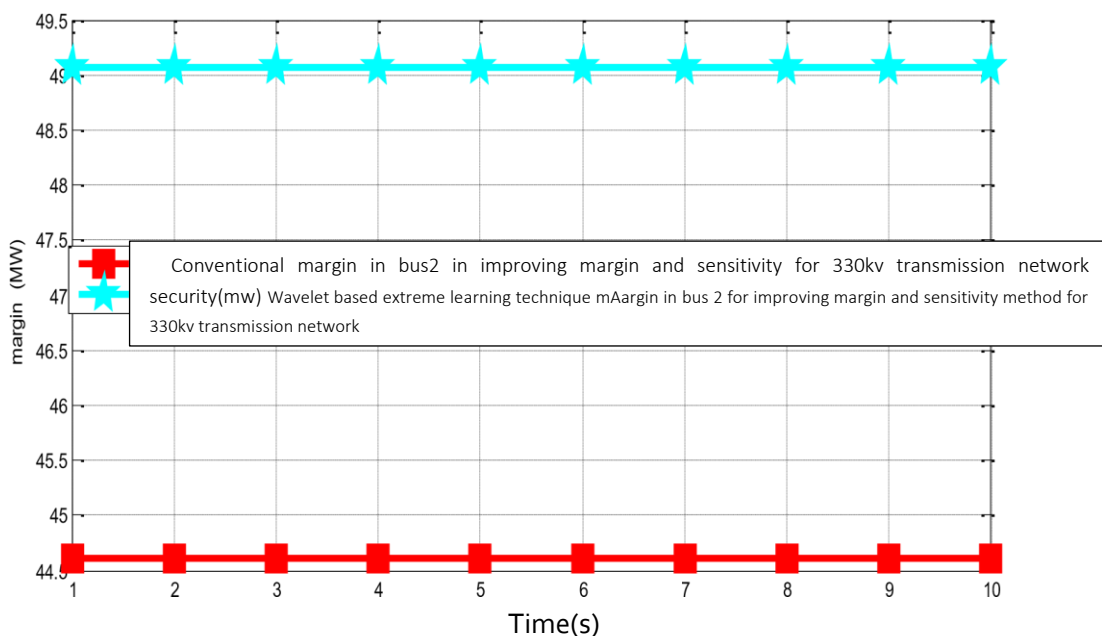


Fig 4.5 comparisons of Conventional and wavelet based extreme learning technique for margin in bus2 in improving margin and sensitivity method for 330kv transmission network security

The conventional margin in bus2 is 44.61MW while when wavelet based extreme learning technique is incorporated in the system it improved to 49.07MW. On the other hand, the percentage improvement in the margin to enhance consistent power supply in 330KV is 10%.

Table 4.6 comparisons of Conventional and wavelet based extreme learning technique for sensitivity in bus2 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 network security transmission	wavelet based extreme learning technique sensitivity in bus1 in improving margin and sensitivity transmission method for 330kv network security ()
1	0.001042	0.001146
2	0.001042	0.001146
3	0.001042	0.001146
4	0.001042	0.001146
10	0.001042	0.001146

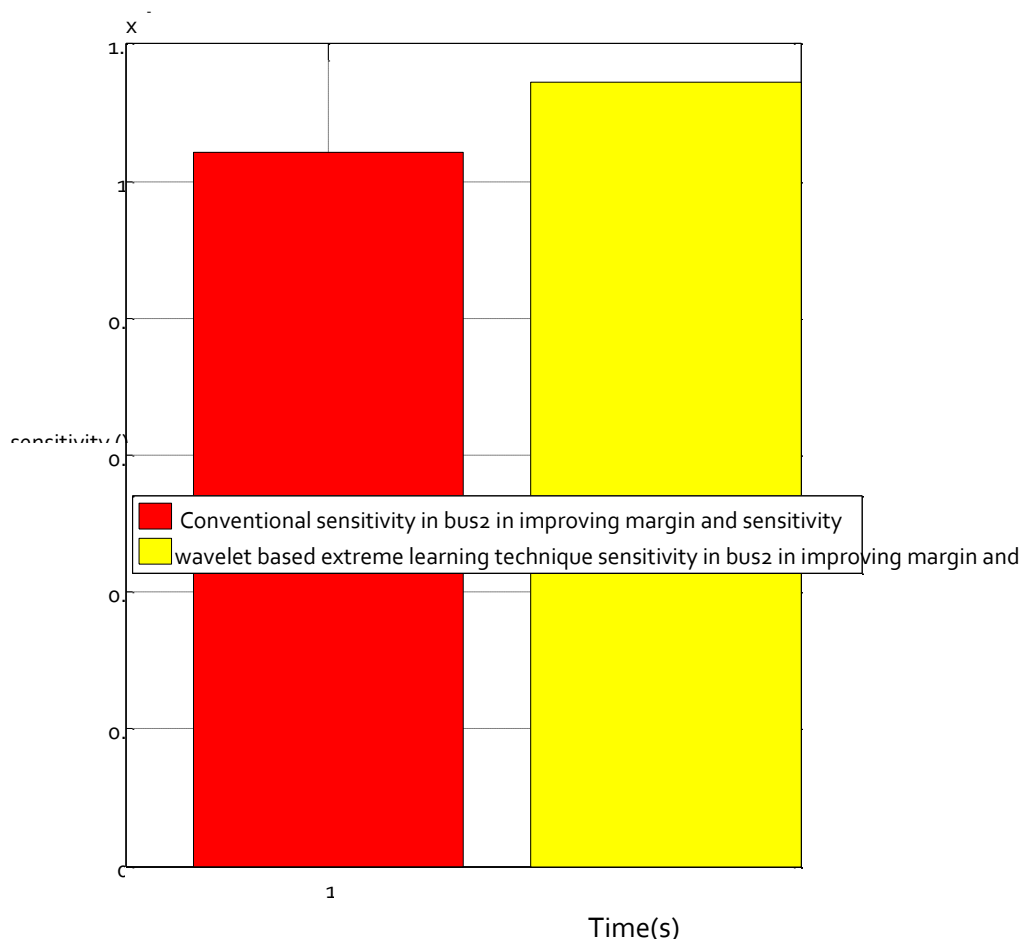


Fig 4.6 comparisons of Conventional and wavelet based extreme learning technique for sensitivity in bus2 in improving margin and sensitivity method for 330kv transmission network security

The conventional sensitivity in bus 2 is 0.001042. On the other hand, when wavelet based extreme learning technique as integrated in the system, it becomes 0.001146 thereby the percentage improvement in the sensitivity in bus 2 when wavelet based extreme learning technique is imbibed in the system is 10%.

Table 4.7 comparisons of Conventional and wavelet based extreme learning technique voltage in bus 6 in improving margin and sensitivity method for 330kv transmission network security

Time(s)	Conventional voltage in bus 6 in improving margin and sensitivity method for 330kv transmission network security (P.U.V)	wavelet based extreme learning technique voltage in bus 6 in improving margin and sensitivity method for 330kv transmission network security (P.U.V)
1	0.880	0.95
2	0.880	0.95
3	0.880	0.95
4	0.880	0.95
10	0.880	0.95

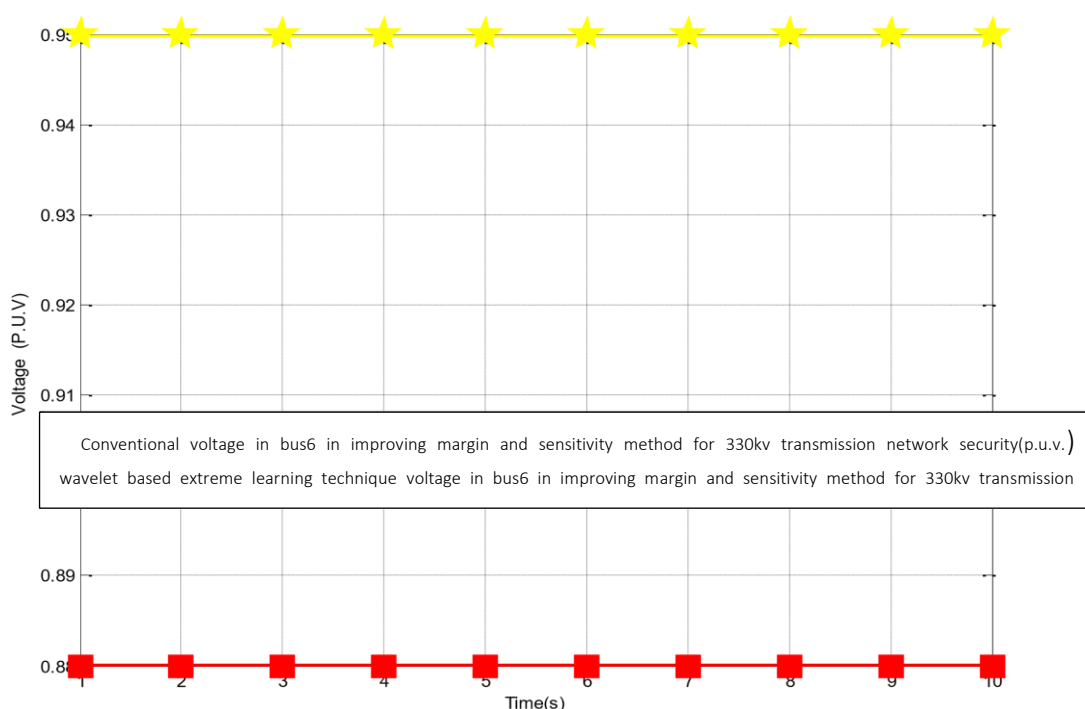


Fig 4.7 comparisons of Conventional and wavelet based extreme learning technique voltage in bus 6 in improving margin and sensitivity method for 330kv transmission network security

The conventional per unit volts in bus 6 is 0.880 while that of wavelet based extreme learning technique is 0.95. The percentage improvement in the per unit volts when wavelet based extreme learning technique was integrated in the system over the conventional approach is 7%.

Table 4.8 comparisons of Conventional and wavelet based extreme learning technique for margin in bus6 in improving margin and sensitivity method for 330kv transmission network security

Time(s)	Conventional margin in bus6 in improving margin and sensitivity method for 330kv transmission network security (MW)	wavelet based extreme learning technique margin in bus6 in improving margin and sensitivity method for 330kv transmission network security (MW)
1	42.31	46.54
2	42.31	46.54
3	42.31	46.54
4	42.31	46.54
10	42.31	46.54

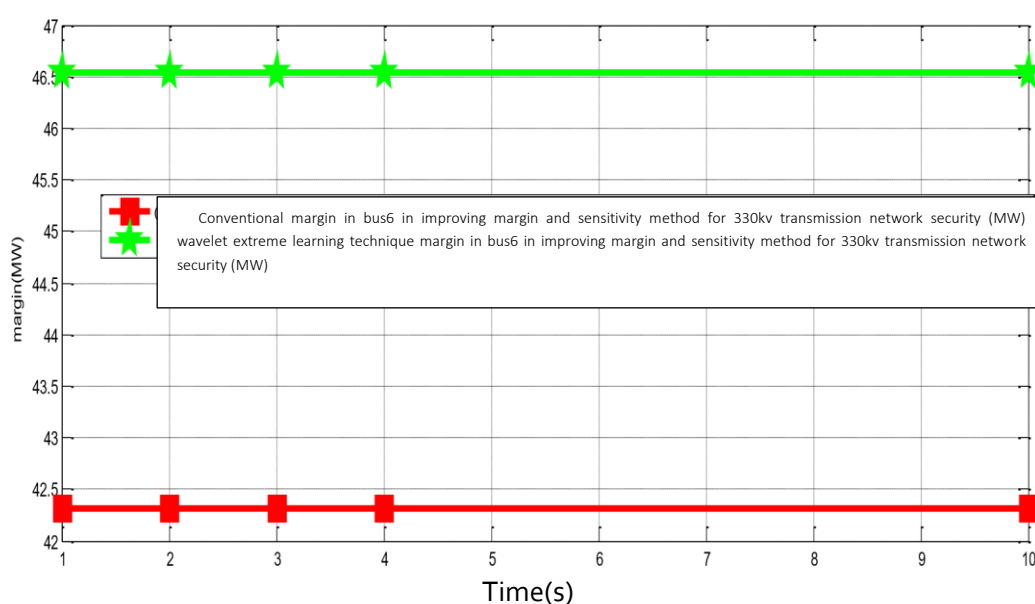


Fig 4.8 comparisons of Conventional and wavelet based extreme learning technique for margin in bus6 in improving margin and sensitivity method for 330kv transmission network security.

The conventional margin in bus 6 of 330KV transmission network that vehemently caused irregular power supply in the network is 42.31MW. Meanwhile, when wavelet based extreme learning technique is incorporated in the system, it automatically increased to

46.54 MW. The percentage improvement in the sensitivity when wavelet based technique is incorporated in the system over the conventional aspect is 10%.

Table 4.9 comparisons of Conventional and wavelet based extreme learning technique for sensitivity in bus6 in improving margin and sensitivity method for 330kv transmission network security

Time(s)	Conventional sensitivity in bus6 in improving margin and sensitivity method for 330kv transmission network security ()	wavelet based extreme learning technique sensitivity in bus6 in improving margin and sensitivity method for 330kv transmission network security ()
1	0.000987	0.001086
2	0.000987	0.001086
3	0.000987	0.001086
4	0.000987	0.001086
10	0.000987	0.001086

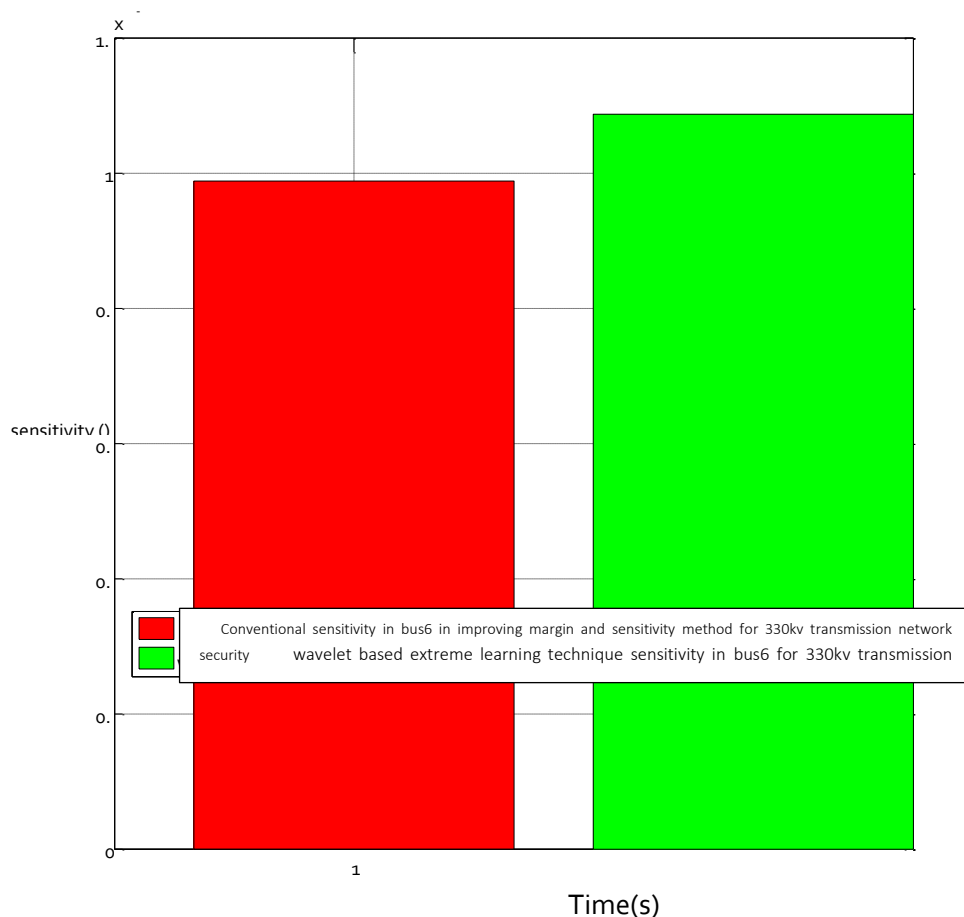


Fig 4.9 bar chart comparisons of Conventional and wavelet based extreme learning technique for sensitivity in bus 6 in improving margin and sensitivity method for 330kv transmission network security

In Fig 4.9 the conventional sensitivity in bus 6 of 330kv transmission network that cause epileptic power supply in the network is 0.000987. on the other hand, when wavelet based extreme learning technique is integrated in the system it increased the sensitivity to 0.001086 thereby tremendously improving constant power supply in 132KV transmission network to the peak.

Finally, the entire system was validated and justified to ascertain the percentage improvement in the margin and sensitivity of the network with and without wavelet based extreme learning technique. This was achieved through the following simple calculations;

$$\frac{\text{Wavelet based Ext. Learning. voltage} - \text{conventional voltage}}{\text{Conventional voltage}} \times 100\%$$

In summary, percentage improvement in power sensitivity when wavelet was incorporated into the system over the conventional approach is 10%.

Concluding Remarks and Contribution to Knowledge

The persistent power failure in the transmission network which has paralyzed economic activities in the country, is caused by low power margin and low power sensitivity. This ugly trend can be surmounted by the introduction of improved margin and sensitivity method for 330kv transmission network security using wavelet based extreme learning technique. To achieve this, we characterize 330KV transmission network and ran the load flow of the characterized network to establish the buses that caused low margin and low sensitivity in the network. We also developed a wavelet rule base that will improve the margin and sensitivity of the network, and trained ANN in the developed wavelet rule base to improve the margin and sensitivity method of the network. The design of a SIMULINK model for wavelet extreme learning technique was done, and the algorithm that will implement the process developed. We then validated and justify the process by calculating the percentage improvement in the margin and sensitivity of the network with and without wavelet extreme learning technique. The results obtained indicates that the improvement in the power margin, voltage and sensitivity in bus 1 when wavelet was incorporated in the system is 9.99%, and that of bus 6 is 10.1% when wavelet was integrated in the system, Finally, the overall percentage improvement in power sensitivity when wavelet was incorporated in the system over the conventional approach is 10%.

The introduction of intelligence in the wavelet through extensive training of ANN in the stipulated rules, boosts the power margin and power sensitivity to enhance stable power supply in the transmission network. It is therefore recommended that power network managers should be grinded in using artificial intelligence to eliminate power failure in the entire power sectors.

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