SIMULATION OF INTELLIGENT UNIFIED POWER FLOW CONTROLLER FOR OPTIMAL POWER SYSTEM SECURITY

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ABSTRACT
This research was targeted at improving the security of the Nigeria 330kv grid network using intelligent margin and sensitivity-controlled fact devices. The study reviewed many literatures and discovered that a system capable of controlling load and stabilizing the grid adequately against collapse is yet to be developed. This challenge was addressed in the research work using top-down design methodology which starts with the formulation of the problem via characterization using Newton Raphson load flow analysis, down to the development of an extreme learning based algorithm trained with data collected from the 36Bus, 330KV transmission network to generate margin and sensitivity algorithm, which was integrated with Universal Power Flow Controller (UPFC) as an intelligent UPFC. This algorithm was integrated as the controller of the UPFC and then applied to the 330kv transmission network bus and tested through simulation. The results reported voltage magnitude within the tolerance of the Nigerian Electricity Regulatory Commission (NERC) standard for stable network, while phase angle was also evaluated and the result also reported a phase shift between current and voltage which implied stable network. System integration of the intelligent UPFC on the 36Bus, 330KV transmission network was performed and the resulted reported an average voltage magnitude of 0.996903pu and phase angle of -13.6728degreee; which all indicated a stable grid network. Secondly, comparative analysis was performed on the grid, with the characterized network and the results reported a percentage improved of 5.7 on the voltage magnitude stability and 52.15% for power control stability improvement with the intelligent UPFC.

Keywords: 330KV transmission network, Voltage magnitude, phase angle, stability, grid, margin and sensitivity

1. INTRODUCTION

Power system today is a key drive of global economy, as all other sectors depend on it one way or another for survival. However, it is unfortunate the power system experiences very little transformation, when compared to other industries that equally drive the economy. In the information and communication sector for instance which has barely lasted four decades, its transformation has revolved from 1G to 5G and even more in other advanced countries (Yahaya, 2017). Today we have the internet of everything, ranging from domestic appliances to even the agricultural sector. So also is the narrative on other key sectors which drive the economy. However, power system which has lasted for about three centuries, and is the live blood which drives other sectors still barley records significant transformation. So many researchers have contributed immensely to boost the sector, but despite their contributions, the reliability of power system all over the world still remains a fairly tale.

According to Eke and Eneh (2007), reliability simply means the availability of a system at every given period of time. This concept is not applicable to the global power system as it suffers many issues with high potential to cause system failure. Reliable operation of electric power networks demand that system frequency, voltages and currents stay within designed limits, as operation beyond them leads to equipment failures and blackouts (Scott, 1998). Power system is made up of the generation, transmission and distribution sections; each of these sections requires huge investment attention, research, update and analysis, and must be married to each other to produce quality supply. Today, many developed countries have recorded great achievements in the generation section and are able to produce enough power to serve the people, despite growing population. However, developing and under developed countries, especially those where population is not controlled like Nigeria still suffer challenges of both inadequate power supply and poor quality of service (Agency Report, 2022). According to Ogbuh and Madueme (2015), this problem of power system inefficiency was attributed to the sporadic increase in population of users over the year, resulting to increase in demand, overloading among other factors which stress the power system and make it work beyond limit, thus exposing it to insecurity threats. Power system is designed to function at a particular specification for frequency, real power, reactive power, voltage magnitudes and phase angles among other load flow parameters. However, when issues such as faults, human error, generator control problem, overload, occurs, it affect the power system network parameters changes and present a major problem of instability.

According to Tajaswini et al. (2007), instability is a process whereby power systems are not able to operate at their desired condition, due to overloading, fault among, imbalance between active and reactive power, other challenges. Samuel et al. (2021) opined that power system stability analysis is security approach which performs parameter estimation of the load flow to predict uncertainties. Some of the major causes of power system instability are poor synchronization, generation outages, inadequate reactive power, poor voltage regulation, poor generator control performance, cascading failure, human error and even cyber attack (Amin et al., 2013) and thus presents the need for power system security analysis. Over time, many techniques have been proposed to improve the analysis of power system such as New line sensitivity index (Samuel et al., 2017), Phasor Measurement Unit (PMU), Real Power (PV) (Tongiti, 2015) and Reactive power (QV) curve analysis, singular value sensitivity, trajectory sensitivity (Lim and DeMarco, 2016), margin and sensitivity method (Scot, 1998). While these studies all focuses on the stability analysis and control o power system network, gap resides in the need for cognitive control, through Margin and Sensitivity (MS). The MS method measures the amount by which system loads or power transfer can change before a security violation is encountered. But the limitation of this technique is that it lacks intelligence as its analysis is based on logical computations using load flow parameters, but can be improved using artificial intelligence.

The application of Flexile AC Transmission Systems (FACTS) has increasingly attracted research attention, especially for stability analysis. For instance (Kowsalya et al. 2010; Enya and Eke, 2022) applied Unified Power Flow Controller (UPFC) for the stability of the Nigeria 132/33KV transmission network through the absorbance or injection of active or reactive power to balance load flow. In another study, Laszlo et al. (2017) and Mark (2019) applied solid state based static var compensator and static var compensator for stability analysis of transmission networks. However, despite the success Nduka and Ilo (2023) argued that while FACTS devices can compensate for losses and stability the grid, they lack adaptive intelligence to adjust to real time behavior of the grid. In addition the devices are slow in response to rapid grid disturbances which requires urgent attention, lack the predictive behavior to facilitate real-time stability of the grid.

Today the use of machine learning algorithms tailored towards artificial neural networks (Islam et al., 2015; Urquidez and Xie, 2016; Hasan et al., 2017; Tongiti, 2015), have achieved greatly contributed in the detection of instability of load flow in power system network; however, most of the time, it is not clear the definition of success for these neural network models. Secondly the reliability of these models are not convincing as they integrity of data used in training them either do not capture the actual behavior of the power system network, or are affected with noise (Saexena et al., 2011). To this end, this research proposes an intelligent margin and sensitivity-controlled FACTS device. To achieve this, the research adopted a wavelet transform filter to decompose the power system network signals and fine-tune for quality, then an extreme machine learning algorithm, of Single Layered Feed Forward Artificial Neural Network (SLFFNN), trained with inverse matrix function is trained for the monitoring and detection of instability on the network through performance estimation. This instability detected will be controlled utilizing UPFC which Enya and Eke (2022) opined to be the best FACTS device sot stability the network.

2. MATERIALS AND METHOD

The application of artificial neural network has remained one of the most promising techniques to solve complex optimization and predictive problems like the power flow studies. However, the main challenge of the conventional neural network models such as the Radial bias function, convolutional neural network, recurrent neural network, multi layered perceptrons among others (Zhenglei et al. 2020; Ahmed et al., 2019; Yong et al., 2019; Xanthoula et al., 2020), remains the delay training time due to the back propagation in the training algorithms such as gradient descent, Lavenberg, etc. generally deployed for optimization of neurons (Kemal, 2020). This optimization problem has hindered the effective performance and application of neural network in providing real time solutions to complex problems like load flow studies. To address this issue, a Single Layered Feed Forward Neural Network (SLFFNN) which has the ability to learn without training algorithm was proposed by (Huang et al., 2006) and called Extreme Learning Technique (ELT). This ELT is the perfect machine learning algorithm which can guarantee real time margin and sensitivity monitoring of the bus voltage profiles at increase load, to ensure system collapse is intelligently prevented. The ELT is a neural network configuration where the input and hidden neurons are defined randomly while keeping the hidden output layer constant. To develop the ELM algorithm for margin and sensitivity of the bus network, a Single Feed Forward Neural Network (SFFNN) configuration in equation 1 was presented as;

$$F_L(x) = \sum_{i=1}^{L} \beta i g i(x) = \sum_{i=1}^{L} \beta i g\left(w_i * x_j + b_j\right), j = 1, \dots \dots, N \qquad (1)$$

Where L is the number of hidden layers, N is the number of the extracted features, ß is the weight vector connecting the ith hidden layer with the output nodes and the threshold of the ith hidden nodes bj; g is the activation function, w is the weights vectors between the hidden and output layers; and x is the input vector.

From the equation 1, the structure shows how the inverse matrix ß was used to replace the training algorithm between each activated input layers. The activation function (g) used the Rectified Linear Unit (ReLU), which was chosen ahead of other types of activation function like the tangent hyperbolic, sigmoid function among others; as it does not suffer convergence problems. The ReLU was presented in equation 2;

$$f(z_i) = = \max(0, z_i) = \begin{Bmatrix} z_i & z_i < 0 \\ 0 & z_i < 0 \end{Bmatrix}, \dot{f}(z_i) = \begin{Bmatrix} 1 & z_i < 0 \\ 0 & z_i < 0 \end{Bmatrix} \qquad (2)$$

From the model, the output of the ReLU looks like linear but in fact it is nonlinear, because the output is 0 when < $0 < 1, z$. This model in equation 2 ensures that the load flow compact features are within the range of 0 and 1, where data in the neurons and the max (0, z) presented the convergence range of the data during training. Having already applied this activation function to the SFFNN model in equation 3, the model can be presented as;

$$H * V = Y \qquad (3)$$

Where Y is the training target matrix, V is the weight vector and H is the hidden layers of the SFFNN activated matrix as;

$$H = \begin{bmatrix} g(a1.x1 + b1) & g(aL.x1 + bL) \\ \vdots & \vdots \\ g(a1.xN + b1) & g(aL.xN + bL) \end{bmatrix} \mathrm{N* L} \qquad (4)$$

$$V = \begin{bmatrix} v_1^T \\ \vdots \\ v_L^T \end{bmatrix} L * m \qquad (5)$$

$$Y = \begin{bmatrix} y_1^T \\ \vdots \\ y_L^T \end{bmatrix} N * \mathrm{m} \qquad (6)$$

Generally, training ELT requires an optimal approximation of the neurons $\mathrm{w_i\, b_i}$ (i=1…………………..N),V from the model in equation 7;

$$||\mathrm{H}(\mathrm{w_i}, \ldots \ldots, \mathrm{w_{N;}}\ \mathrm{b_i}, \ldots, \mathrm{b_N})\mathrm{V\text{-}Y}|| = \min_{\mathrm{w_i\, b_i\, t}} ||\mathrm{H}(\mathrm{w_i}, \ldots, \mathrm{w_{N;}}\ \mathrm{b_i}, \ldots, \mathrm{b_N})\mathrm{V\text{-}Y}|| \qquad (7)$$

H was obtained from the gradient based training algorithm which was used to minimize the value ‖HV-Y‖. The weights of the input and output ($\mathrm{w_i}$ β_i) and the hidden layer parameter are used to obtain the optimization solution via iterative adjustment as;

$$Q_k = Q_{k-1} - \eta \frac{\partial E(Q)}{\partial\ (Q)} \qquad (8)$$

Where η is the learning rate, Q_k is the weights and bias parameters, ∂E(Q) is the partial derivation of the loss function with respect to the weight and bias parameters, E is the loss function, the use of other training algorithms like the back propagation, gradient descent, can also be used to achieve this optimization in the SLFFNN.

In ELT, Huang et al., (2006) used inverse matrix of Moore-Penrose generalization (Campbell and Meyer, 1991) solution to train H. In the application of the inverse matrix, only the hidden layers output matrix which can be randomly determined at the initiation of the learning process is inverted in the matrix as;

$$\mathrm{V} = H^{\dagger}T \qquad (9)$$

Where $H^{\dagger}$ is the inverse of H with the generalized Moore-Penrose function; the model in equation 9 was used to generate the load reference algorithm used as a reference point for the margin and sensitivity analysis of the bus network.

2.1 The Universal Power Flow Controller (UPFC)

The UPFC is the adopted FACT device in this research for the control of instability on the transmission network bus, through power flow and voltage profile control, through the application of three main components which are control system, shunt inverter and series inverter (Adnan and Alsammak, 2020). The shunt converter (inverter) is the electronics device of the UPFC which bus applied or the control of voltage magnitude at a specific bus o the power system network. This system is triggered when the voltage magnitude of the bus falls below 0.95pu and the bus becomes weak; when triggered, it injects reactive power, which then improves the voltage profile of the network. In addition, when the voltage profile is high above 1.05pu, it absorbs the reactive power and normalizes the voltage profile and the bus stability. This shunt converter overall is used in the UPFC for voltage stability through the control of voltage deviation at the bus (Enya and Eke, 2022). The series converter (Inverter) is the electronics component in the UPFC which is responsible for power control, through the adjustment of impedance affecting the power in the transmission line. This is achieved through the injection or absorbance of real power of the lines. When active power is injected, it improved the impedance on the transmission line and vice versa when it absorbs the active power. The aim is to ensure précised control of power low in the transmission network through the adjustment of the line impedance and ensure grid stability and management of oscillation in the network. The control system monitors the performance of the transmission line and the bus behavior, using the Proportional integral derivative (PID) algorithm to determine the condition of the transmission networks and the bus in the network and control using shunt and series converters (Al-Mawsawi, and Qader, 2003).

2.2 Implementation of the System

The intelligent margin and sensitivity controlled system was implemented on a 330/132kv transmission network with 5 interconnected bus, and two generators. The tool used for the implementation are the power system toolbox, statistics and machine learning toolbox, neural network toolbox, wavelet toolbox, optimization toolbox, database toolbox and Simulink. The power system toolbox was used to implement the model of the multi area power system generators under instability introduced due to impedance mismatch respectively. The wavelet toolbox was utilized to implement the filter which decomposes the power flow on the network. The statistic and machine learning toolbox was used by the neural network toolbox to extract the decomposed signal, while the neural network toolbox was used to train the extreme learning algorithm and generate the margin and sensitivity model which was integrated on the UPC using the optimization toolbox and then applied to the bus of the transmission network to monitor and stability the bus during instability period. The figure 1 presents the simulated Nigeria 330KV transmission network considering 5 buses, with the UPFC.

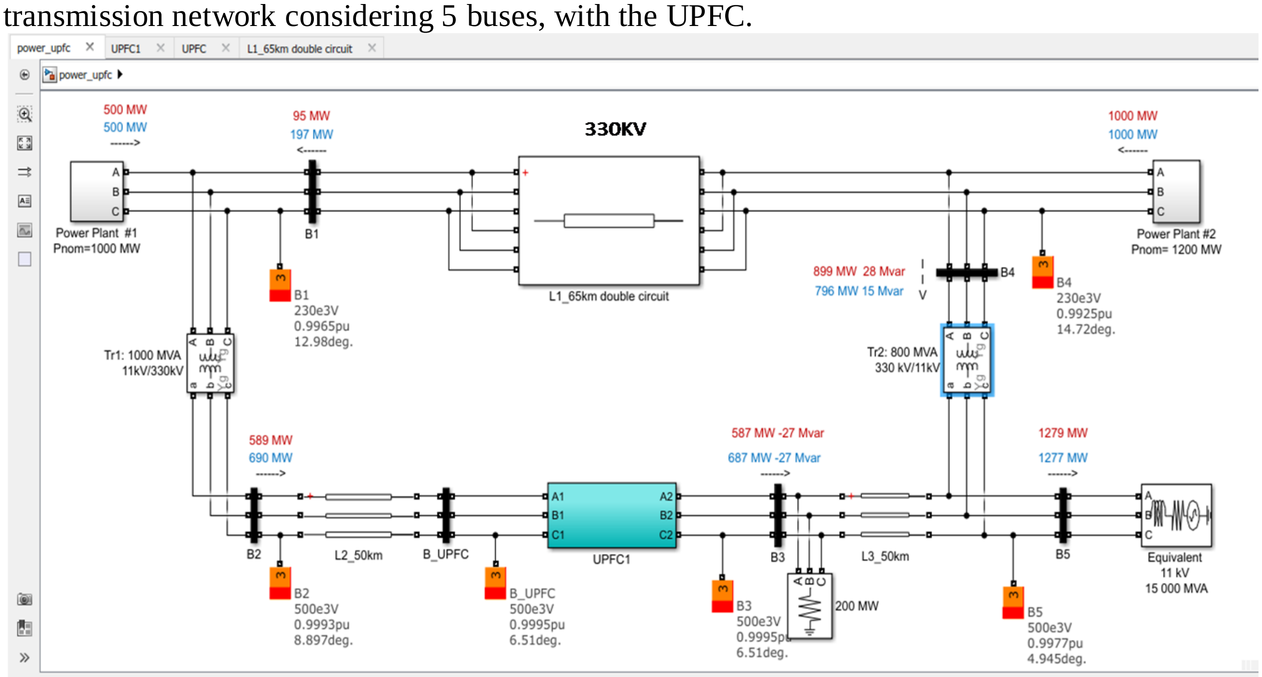

Figure 1: Simulink model of the transmission network with intelligent UPFC

The Simulink model showed the transmission network with two generators and 5 buses and the UPC bus connected to the transmission network for stability control. The two generators generated power of 100MW and 1200MW which were respectively stepped up by the two power transformers and transmitted to the secondary transmission station which five buses were reported as shown. While the generators supplied the desired power to the network, various factors such as lack of synchronism, faults, etc can affect the power quality, which in-turn affects the bus stability. The UPFC developed with the margin and sensitivity control algorithm identified this problem and then injects or absorbs active or reactive power to stability the network.

3. RESULTS AND DISCUSSIONS

The results began with the performance of the neural network algorithm trained as an extreme learning technique to facilitate fast margin and sensitivity of the load flow. The training utilized metrics such as accuracy, precision, recall, and cross entropy to evaluate the model performance. The results obtained were cross validated in 5-folds and reported in table 1.

Table 1: Result of the Extreme learning training

Fold	Accuracy	Precision	Loss	Recall	ROC
1	96.80	97.53	0.0046463	95.05	0.96
2	96.45	98.70	0.0087634	93.39	0.95
3	98.37	98.66	0.0054345	95.57	0.97
4	97.21	98.19	0.0043765	96.29	0.98
5	98.70	96.37	0.0032535	93.70	0.90
Average	97.506	97.89	0.005295	94.8	0.952

The table 1 presents the performance of the extreme learning algorithm used for the optimization of UPC. From the results, it was observed that on the average, the success rate of the model to correctly sense the instability on the grid is 97.506%, positive classification of grid behavior recorded 97.89%, correct classification of instability on the grid recorded 94.8% and the receiver operator characteristics curve which model the relationship between the true positive and false positive recorded 0.952, which all collectively point to a very good model or the detection of grid behavior in diverse conditions. The next result presents the performance of the UPFC during power flow and voltage control to stabilize the network.

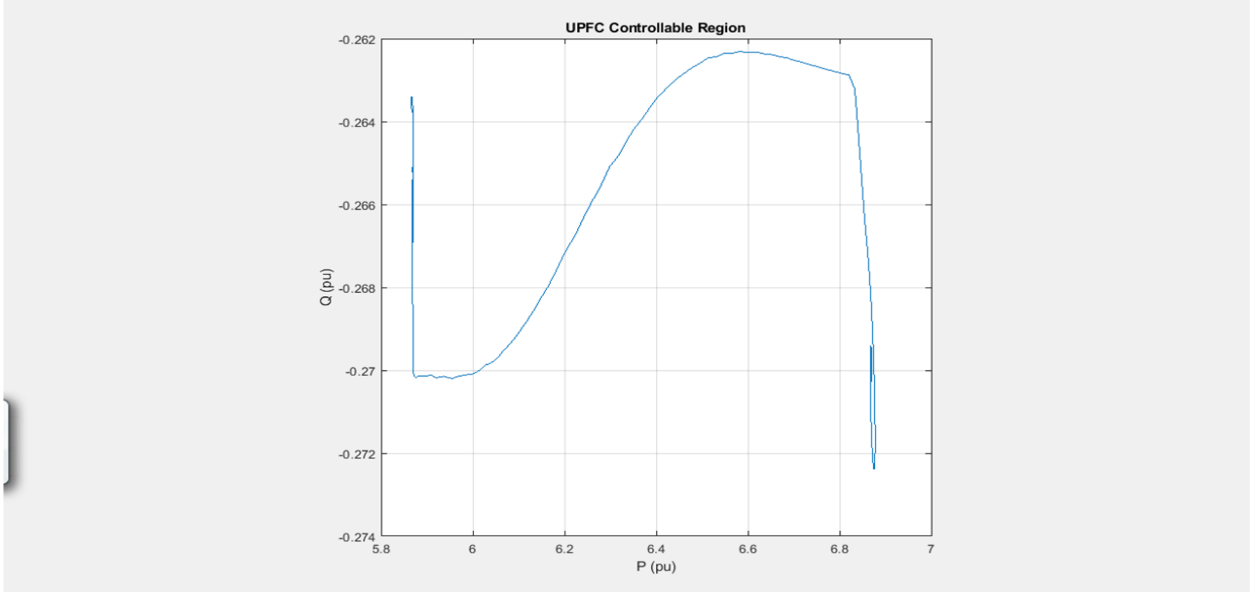

Figure 2: The UPFC Control performance

The figure 2 which showed the control operation of the UPFC, it was observed that the system was able to adjust reactive power (Q) and active power (P). It shows how Q and P are exchanges based on the power flow on the network achieve stability. The reactive power are injected or absorbed with the shunt converter which monitors the level of voltage magnitude and then adjust the reactive power to control it using the margin and sensitivity algorithm. Similarly is the phase angle which monitors the power flow stability and use the active power to control it. The next section demonstrates the effectiveness of the intelligent UPFC on a 330KV transmission network and then evaluated considering 5 bus under the condition of transient stability.

3.1 Simulation Result of the 330KV Network simulation with Intelligent UPFC

This section demonstrates the effectiveness of the intelligent UPFC on the transmission network during normal and unstable condition due to the impedance mismatch of the two generators. The reactive power flow of the bus after 20 minutes of simulated operation was presented in the figure 3;

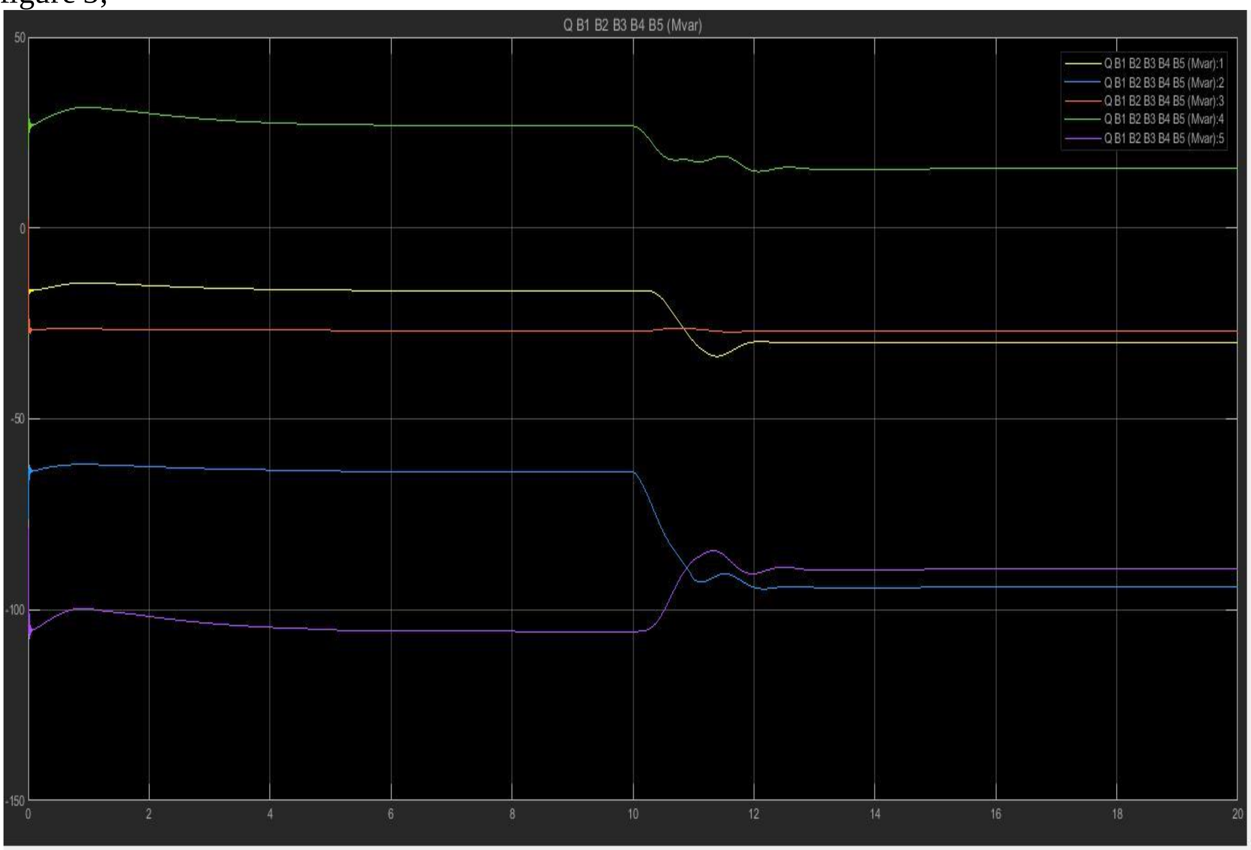

Figure 3: The transmission network bus with reactive power flow

The figure 3 presented the reactive power flow of the 5 bus during transient stability. From the result it was observed that after 10 minutes of load flow, thee was instability on the lines which affected the bus, but was corrected by the UPFC immediately. What this means is that the reactive power imbalance was detected by the margin and sensitivity algorithm trained with the extreme learning techniques, then the shunt converter was activated to control the power flow through the injection of reactive power and then us stabilizes. In the figure 4, the active power flow performance was also investigated with the UPFC.

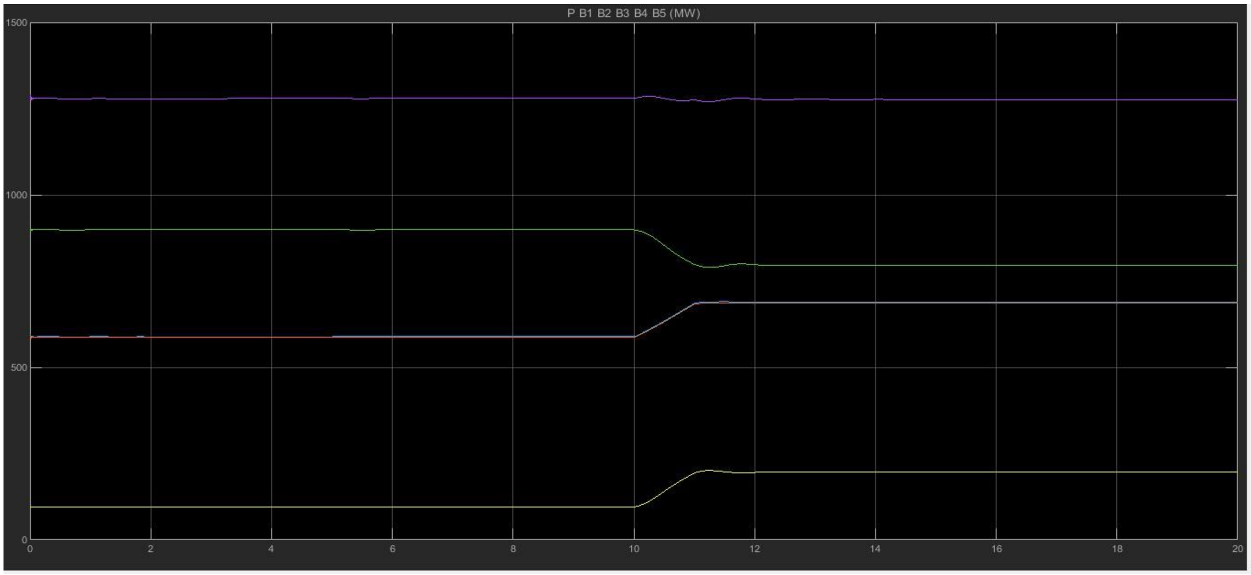

Figure 4: The transmission network bus with active power flow

From the result in the figure 4, which showed the five bus performance with UPFC, it was observed that during the load flow of the network, it 10minutes, the uses experiences changes on the active power. The reason was due to impedance imbalance of the supplied generated with the load, which affects the phase angle and results to the problem experienced in the active power flow. To control it, the margin and sensitivity algorithm detects the load flow impedance and phase angle to detect the instability and activate series converter which injected active power to control the power flow.

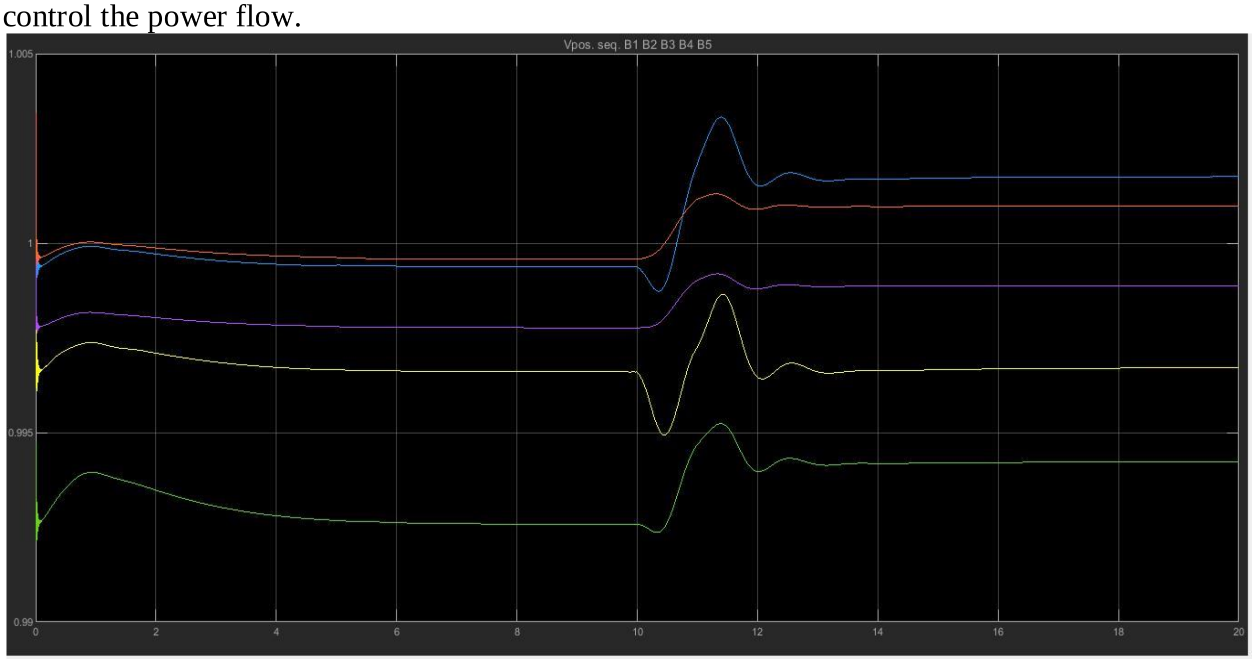

Figure 5: The transmission network bus with their voltage magnitude

The figure 5 presented the transmission network bus voltage profile during the transient stability condition. From the result it was observed that the voltage magnitude of the bus was stable until 10mins, when instability was introduced due to generated impedance mismatch with the load, and the implication resulted to alteration of the load flow pattern as observed at 10, however the changes was detected by the margin and sensitivity algorithm incorporated with the UPFC and then and then shunt converter was activated to control the load, as depicted after 12mins when the imbalance was controlled for all the bus. The figure 6 presets the phase angle of the transmission network bus, while figure 7 presents the performance of the UPFC during the detection of the load flow unstable condition.

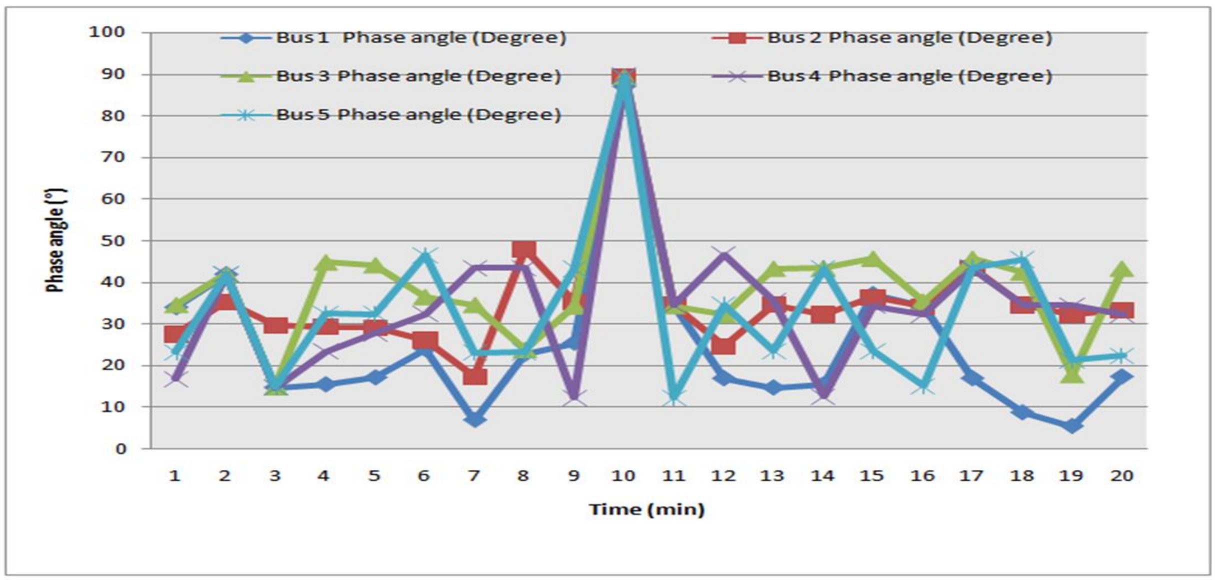

Figure 6: The transmission network bus with their phase angle

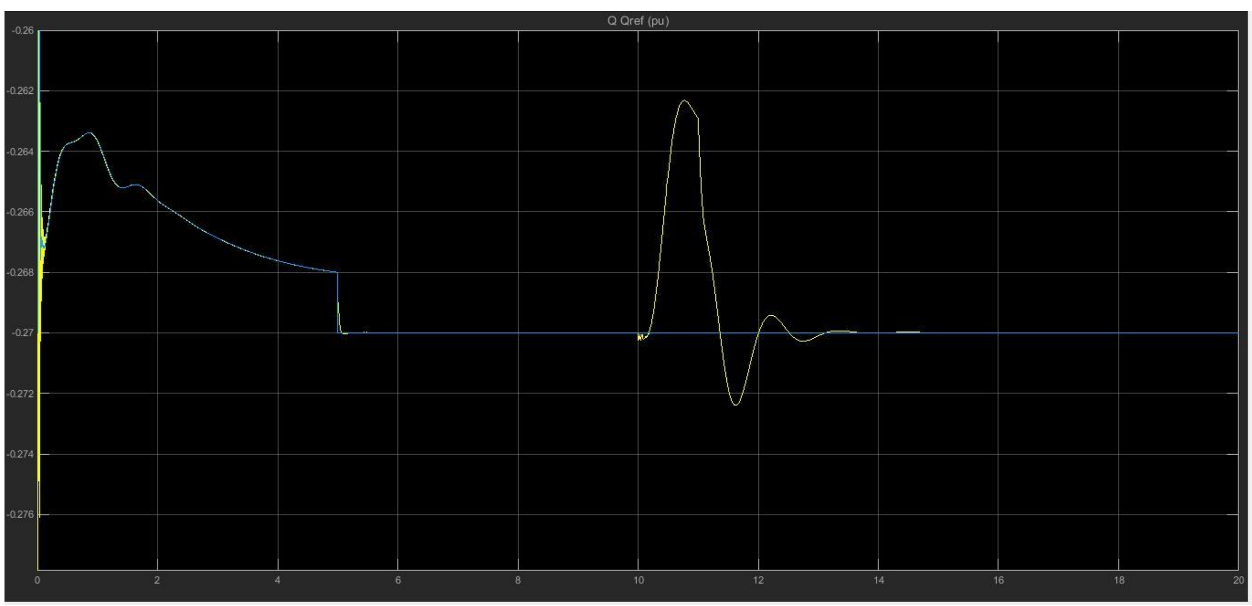

Figure 7: The UPFC control performance

From the figure 6, the phase angle for all the bus at various times of the load flow was reported and it was observed that from the five bus, it was observed that all the bus reported phase angle below 50degree which is good and indicates stable power flow network; however at 10min, it was observed that the phase angle changes to a very high level approach 90degree which indicated instability, but at 11 minutes the phase angle returned based to stable margin. What this mean is that at this point, the margin and sensitivity detected the deviation and injected the series converter which absorbed the active power to stability the bus, thereby restoring the phase angle to normal. The figure 7 presents the performance of the UPFC during the detection of the load flow unstable condition. In the figure 7, two lines are presented (blue which is the reference reactive power per unit) and then (yellow) the present reactive power as the load flow continues. Due the detection, the margin and sensitivity identified these signal and compared with the reference trained signal with extreme learning technique to intelligently detect the imbalance, while the appropriate convert is activated to control the instability and prevent grid collapse.

4. CONCLUSION

The population of Nigeria keeps increasing on daily basis and also the rapid exodus of people from one area to another (urbanization) in search of greener pastures. This proportionally, changes the load behavior of power systems on daily basis and presents the need for continuous network monitoring to control overload. When load changes due to increased power consumption or demand, the voltage profile becomes quadratic, thus leading to many inimical issues, to the behavior of the grid. Other causes of instability on the network include frequency deviations, voltage control problems, reactive power control inadequacies, communication failures, transformer issues, and inaccurate grid modeling. Based on this evidence, t is clear that instability is inevitable in every power system; however it can be managed to reduce its impact on the network and also customers. The research developed a security algorithm extreme learning technique that employed inverse matrix function to train a single feed forward neural network with data of instability collection from the grid. The algorithm generated was implemented with Matlab, simulated and validated on an uncontrolled interconnected bus network. The result showed that the quadratic voltage data due to instability was detected on the network in real time and then UPFC shunt and series converter components were triggered to control the load flow.

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