MODELLING OF AN INTELLIGENT VIRTUAL POWER PLANT FOR OPTIMAL ENERGY NETWORK MANAGEMENT AND CONTROL USING MACHINE LEARNING TECHNIQUE

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ABSTRACT

This paper presents the modeling of an intelligent virtual power plant for optimal energy network management and control using machine learning techniques. The aim is to present a system that can collect data from the grid and interpret it to make control decisions that improve the quality of service on the Nigerian 36-bus, 330KV interconnected transmission network. In the study, an observation and simulation approach was used as the research methodology. The methods used were data collection from the National Control Centre (NCC) Oshogbo with Newton-Raphson load flow analysis, data processing with a shunt active filter, the Power Flow Reference Model (PFRM), the Intelligent Load Flow Control System (ILFCS), and the and the Intelligent Virtual Power Plant (IVPP). The PFRM was modeled with the Back Propagation Feed Forward Neural Network (BNN) to develop the intelligent monitoring system; the ILFCS was modeled with the PFRM and the Nigerian Electricity Regulation Commission (NERC) standard for voltage stability to develop the control algorithm. The PFRM and ILFCS were used to model the IVPP. The IVPP was implemented with MATLAB and tested. The result of the PFRM measured with Mean Square Error (MSE) was 5.623e-06Mu, which is good as it is approximately the ideal MSE value, which is 0. The regression (R) performance was 0.9999, which is good as it is approximately the ideal R of 1. The implications of these results showed that the PFRM was able to learn the patterns of the load flow correctly and was able to detect changes on the grid with respect to the voltage profile. The performance of the ILFCS showed that the load flow from the grid was intelligently monitored, and then the unstable bus was controlled, while those at their stability limit were also addressed.

Keywords: Energy Network Management; Machine Learning; Intelligent Load Flow Control System; Intelligent Virtual Power Plant

1. INTRODUCTION

Over the years, the need for sustainable electricity has triggered the exploitation of various alternative measures to help boost power supply in various parts of the world. The conventional approach to power generation, which employed the use of hydropower plants, gas plants, thermal plants, and nuclear plants, involved huge investment costs to actualize and, even more, to produce enough power to satisfy the ever-increasing global population. However, these means of power generation, despite their success so far, are not without their limitations, and environmental pollution is among the major problems that trigger climate change (Sergi, 2017).

According to the 26th United Nations Climate Change Conference (2020), climate change has remained a global concern all over the world, and the traditional means of power generation have worsened these issues with the huge contribution of carbon (IV) oxide, among other air pollutions, into the atmosphere, thus increasing the effects of climate change and upsetting the peace of the ecosystem at large. To address this problem, various administrative measures have been proposed (Andre et al., 2018), with the use of renewable energy among the solutions to reduce pollution caused by power generation.

Renewable energy is a form of energy generated from natural sources like the sun, water, fossil fuels, wind, and biomass, among others (Moh et al., 2018). These various sources of renewable energy all have their advantages and disadvantages. Hydro is sustainable, as the water can be recycled, but the implementation cost is very expensive. Biomass and thermal energy required huge space and initial capital for implementation. The wind and solar provide vital features such as efficiency, sustainability, space, and low cost of implementation, but they are weather and climate dependent. Nevertheless, these renewable energy forms (solar and wind), due to their advantages over others, have provided opportunities for private parties to generate their own power source and integrate it into the grid through a distribution generator (DG).

This DG allows multiple small-scale generators that produce energy in various forms to be integrated into the grid to boast supply capacity in a decentralized approach, thereby providing energy for rural locations and improving the efficiency of power supply. However, there is a small number of DGs installed, which, as a result, makes them invisible to the grid load pattern in developing countries like Nigeria. As a result, little pressure is put on the need to notice their impact on the overall grid, even though it is very important for better management; hence, there is a need for a system that effectively manages all the DGs within the grid, and this can be achieved using smart grid systems (Andre et al., 2018).

According to Sergi (2017), the smart grid is the future electrical grid that will use information and communication technology (ICT) as a vehicle to handle a large amount of distributed energy resources (DER) to increase the efficiency and reliability of the overall power system. This SG has the potential to integrate all the DGs into a singular system and effectively manage demand through a process called Virtual Power Plant (VPP). This VPP simplifies the electrical network by amalgamating all the DGs units into one virtual box, which is easier to work with than many hundred or thousand small units. This VPP is classified as commercial and technical. The technical type is responsible for the management of the demand side using information collected from distribution network operators, while the commercial type is responsible for the trading entity of the power system. However, the limitation of this VPP is their ability for effective demand-side management due to the variation of power generated (Yang et al., 2019; Hu et al., 2019; Kong et al., 2019; Sun et al., 2019). As already identified, this VPP integrates all DER together, which are dependent on various renewable energy sources like wind, sun, etc. These energy sources vary with time and hence fluctuate all the time, thus affecting the quality of power generated. On a wider scale, the low loading factors combined with the uncertainty in their individual outputs lead to an excess of generation from centralized sources and hence affect the quality of demand-side management (Andre et al., 2018). To address this problem, it is vital for a system that has the ability to estimate future DER behaviors to improve the performance of

VPP management. According to Kong et al. (2019), this can be achieved using load forecasting. Load forecasting is a technique employed by power system companies to predict the time series of energy required to better manage demand and supply at all times. They are of many types, such as long-term, medium-term, short-term, and very short-term. According to Dagdougui et al. (2019), the most effective is the short term, due to the close relationship between the actual data and the estimated values when tested, compared to the rest. Recently, these techniques have been employed to improve the performance of VPP using various methods like genetic algorithms, machine learning, and fuzzy logic (Kong et al., 2019; Sun et al., 2019; Huang et al., 2019; Cai et al., 2019), among other mathematical optimization approaches (Ouyang et al., 2019; Hu et al., 2019), but despite the success, the estimated power of the collective grid and the actual power vary significantly, which is not good. Other techniques suffer delay in training time and unreliability, among many other challenges, which gives room for the development of an advanced VPP system for optimal virtual power plant management. Nevertheless, the use of machine learning provided better performance compared to its other counterparts. Machine learning is a branch of artificial intelligence that has the ability to learn and make accurate decisions (Kong et al., 2019). They are of the supervised and unsupervised types, with numerous algorithms embedded in each. This paper proposes the use of an unsupervised machine learning algorithm to develop an intelligent VPP system for better energy management performance.

2. METHODOLOGY

The methodology used experimental approach while the research methodology is waterfall model. The research methods are characterization of the Nigerian national grid via load flow analysis, model of the power flow formulation, power low regression model, intelligent load flow control system, intelligent VPP model and then implementation with high level programming language.

3. MODELLING OF THE POWER FLOW FORMULATION

The idea in this section was to present the relationships between the power flow parameters on the transmission lines and their buses using load flow analysis. The power flow in the n bus admittance matrix Y as equation 1 which was represented in polar form as equation 2 (Ogbuefi and Madueme, 2015);

$$I_i = \sum_{j=1}^{n} Y_{ij} V_j \quad 1$$

$$I_i = \sum_{j=1}^{n} \left|\left|Y_{ij}\right|\right| V_j| < (\theta_{ij} + \delta_j) \quad 2$$

Where I and j are $i^{th}$and j^{th} bus respectively,$|Y_{ij}|$is the admittance matrix. The active and reactive current flow is presented with equation 3;

$$I_i = \frac{P_i - JQ_i}{V_i} \quad 3$$

Substituting the models in equation 2 and 3 presented the equation 4 and 5;

$$P_i - JQ_i = |V_i| < - < \delta_i \sum_{i=1}^{n} \left|\left|V_j\right|\right| Y_{ij}| < (\theta_{ij} + \delta_j) \quad 4$$

$$P_i - JQ_i = \sum_{i=1}^{n} |V_i V_j Y_{ij}|| < (\theta_{ij} + \delta_j) \quad 5$$

The real and imaginary parts of the power flow were separated as;

$$P_i = \sum_{i=1}^{n} \left|V_i V_j Y_{ij}\right|| \cos(\theta_{ij} + \delta_j + \delta_i) \qquad 6$$

$$Q_i = \sum_{i=1}^{n} \left|V_i V_j Y_{ij}\right|| \sin(\theta_{ij} + \delta_j + \delta_i) \qquad 7$$

Where $|V_i|$ is he voltage magnitude at bus i, I_i is the conjugate current magnitude at bus i, P_i is the per unit injected power at bus i, Q_i is the per unit injected reactive power at bus i, δ_i is the phase angle at bus i and δ_j is the phase angle at bus j. From the model in equation 6 and 7, it was observed that the variables of the load flow are unbalanced.

3.1 Newton Raphson Load flow Model

To address this problem the application of numerical method was employed which used Newton Raphson techniques to approximate the power flow problem formulation. This was achieved using applying Taylor series expansion on the imaginary power flow in 6 and 7 to presents the matrix Jacobian equivalent as (Ogbuefi and Madueme, 2015);

$$\begin{bmatrix} \frac{dP_2}{d\delta_2|} & \frac{dP_2}{d\delta_2|} & \frac{dP_2}{d|V_2|} & \frac{dP_2}{d|V_n|} \\ & & & \vdots \\ \frac{\frac{dP_n}{d\delta_2}}{\frac{dQ_2}{d\delta_2}} & \frac{dP_n}{d\delta_n} & \frac{dP_2}{d|V_2|} & \frac{\frac{dP_2}{d|V_2|}}{\frac{dQ_2}{d|V_n|}} \\ & \frac{dQ_2}{d|\delta_n|} & \frac{dQ_2}{d|V_2|} & \vdots \\ \frac{dQ_n}{d\delta_2} & \frac{dQ_n}{d\delta_2} & \frac{dQ_n}{d|V_2|} & \frac{dQ_n}{d|V_n|} \end{bmatrix} \begin{bmatrix} \Delta\delta_2 \\ \vdots \\ \Delta\delta_n \\ d|V_n \\ \vdots \\ d|V_n| \end{bmatrix} = \begin{bmatrix} \Delta P_2 \\ \vdots \\ \Delta P_n \\ \Delta Q_n \\ \vdots \\ \Delta Q_n \end{bmatrix} \qquad 8$$

Linearizing the matrix formulation presented the Jacobian matrix between variations in the phase angle and voltage magnitude with respect to the changes in real and reactive power. These were modified as;

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} J_1 & J_2 \\ J_3 & J_4 \end{bmatrix} \begin{bmatrix} \Delta\delta \\ d|V_n| \end{bmatrix} \qquad 9$$

Where $\Delta\delta_I$ is the change in phase angle, $\Delta|V_i|$ is the change in voltage magnitude, ΔP_i is change in real power and ΔQ_i is variation in reactive power. The diagonal and off diagonal J_1 elements of the Jacobian are presented as;

$$\frac{dP_i}{d\delta_i} = \sum_{j \neq i} \left|V_i V_j Y_{ij}\right|| \sin(\theta_{ij} + \delta_j + \delta_i) \qquad 10$$

$$\frac{dP_i}{d\delta_j} = -\left|V_i V_j Y_{ij}\right|| \sin(\theta_{ij} + \delta_j + \delta_i) \qquad 11$$

Where j ≠I,

$$\frac{dQ_i}{d\delta_j} = \sum_{j=1}^{n} \left|V_i V_j Y_{ij}\right|| \sin(\theta_{ij} + \delta_j + \delta_i) \qquad 12$$

Similarly, the diagonal matrix for of J_2 J_3 J_4 elements is;

$$\frac{dP_i}{d|V_i|} = 2|V_i + Y_{ii}|COS\theta_{ii} \sum_{j=1} \left|V_i V_j Y_{ij}\right|| \cos(\theta_{ij} + \delta_j + \delta_i) \qquad 13$$

$$\frac{dP_i}{d|V_i|} = \left|V_i Y_{ij}\right|| \cos(\theta_{ij} + \delta_j + \delta_i) \qquad 14$$

$$\frac{dQ_i}{d\delta_j} = \sum_{j \neq 1} \left|V_i V_j Y_{ij}\right|| \cos(\theta_{ij} + \delta_j + \delta_i) \qquad 15$$

$$\frac{dP_i}{d\delta_j} = -\left|V_i Y_{ij}\right|| \cos(\theta_{ij} + \delta_j + \delta_i) \qquad 16$$

$\frac{dQ_i}{d|V_i|} = -2\left|\left|V_i Y_{ij}\right|\right| Y_{ij} sin\theta_{ii} + \sum_{j\neq 1} |V_i||Y_{ij}| \sin\left(\theta_{ij} + \delta_j + \delta_i\right)$ 17

$\frac{dQ_i}{d|V_j|} = -|V_i||Y_{ij}| \sin\left(\theta_{ij} + \delta_j + \delta_i\right)$ 18

While ΔP_i and ΔQ_i in equation 9 are the changes between the scheduled and calculated power

$\Delta P_i = P_i^{sch} - P_i$ 19

$\Delta Q_i = Q_i^{sch} - Q_i$ 20

From the models in equation 9, 19 and 20 the change in phase angle and voltage profile are also calculated to complete the iteration process. The next values of the k+1iterations are presented as;

$\delta_i^{k+1} = \delta_i^k - \Delta\delta_i^k$ 21

$|V_i^{k+1}| = \left|V_i^k\right| - |\Delta V_i^k|$ 22

3.2Modelling of the Virtual Power Plant (VPP)

The VPP model was developed using architectural diagram in figure 1 which employed information generated from the load flow for energy management with respect to the generation, transmission and distribution networks respectively.

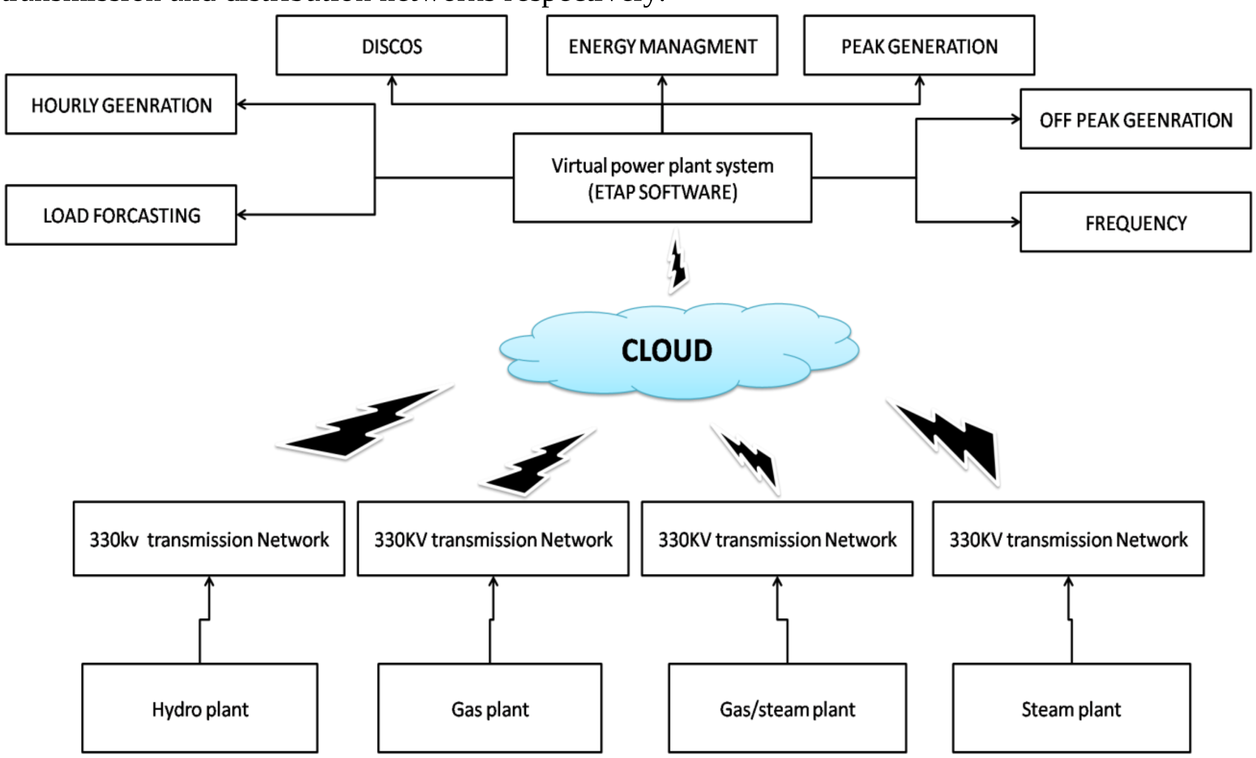

Figure 1: Modeling diagram of the VPP

From the VPP model, the power generated from the various generating plants and transmitted to the grid were monitored and then managed. From the VPP model, vital information of the power generation was determined such as the peak generation, frequency, hourly generation, off pick generation, etc. the behaviour when transmitted on the 330KV grid was also monitored using the load flow analysis formulation. From the data collected, decisions are made manually or damned side management by the managers and power system operators.

4. THE INTELLIGENT LOAD FLOW CONTROL SYSTEM (ILFCS)

Before the development of the ILFCS proceeds, one can question its justification as there is fault detections system and power flow control solutions installed at the substation. This is true but the systems both for faults and power flow control are all programmed and are sensitive, but lack intelligence. Secondly, they are limited to the specific of load flow for fault and cannot detect a nonlinear issue which gradually builds to these problems. This is why today there are issues of power fluctuations everywhere, over or under current supply, among other issues which characterize the Nigerian power system quality as one of the worst in the world. The new ILFCS has come to solve these issues with the capacity to notify operators of arising challenges on the network from the generation down to the transmission sections.

4.1 Data Collection

Data of the 330KV load flow was collected at NCC containing bus information and power flow data. The data was collected using the ETAP load flow software from 14th June, 2022 till 14th July 2022. The data collection considered attributes unstable bus voltage profile, stable bus voltage and marginal bus voltage (i.e those at the exact tolerance margin or instability). The standard for the data collection was guided by the Nigerian Electricity Regulatory Commission (NERC) which stated $\pm$ 5% (1.0000p.u) for voltage profile.

4.2 Power Flow Regression Model (PFRM) for load flow monitoring

To develop a system which is autonomous, it must have the ability to make time series predictions based on past behaviour of the grid. The idea is to read in step ahead the issues of instability and faults on the grid before they turn to major problems and notify the system operators for fast control solutions. To this end the Back-Propagation Neural Network (BNN) model was used to train the respective data collected. The reason for this was due to the dynamic and continuous behaviour of load flow and hence requires a system which can make predictions based on its past behaviour, hence memory to retain the past load flow information is required so as to predict future behaviour. Conventional feed forward neural network which can solve this problem, lacks memory, back propagation was used to retain the past information of the load flow while training and making time series decisions.

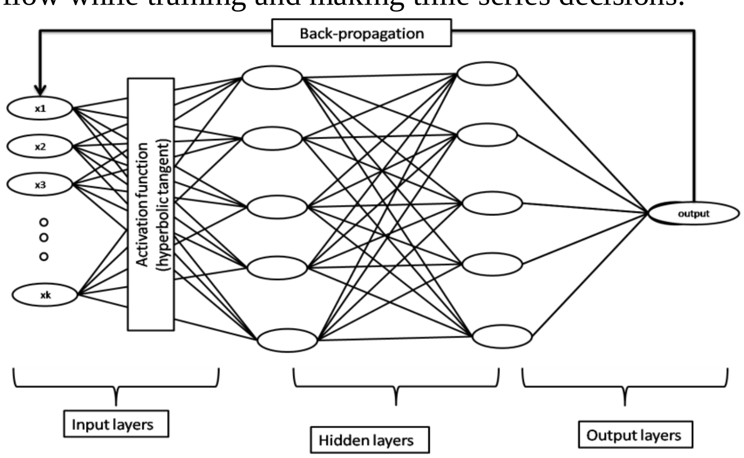

Figure 2: Model of the BNN

The model of the BNN was developed from feed forward neural network algorithm adopted from Ogboh and Madueme (2015). The algorithm neuron (x) was made up of weight and bias, the activation used to activate the neuron is hyperbolic tangent (Tanh), and the numbers of neurons were decided based on the attributes of the data collected which are voltage per unit, frequency, active power, reactive power and power factor.

4.3 Training of the BNN for the Power Flow Regression System

To train the BNN, the data collected was loaded on the model in figure 2, and then a training algorithm (Gradient descent) was used to train the neurons until the data was learned and the regression algorithm was developed. The model or the training was presented in figure 3;

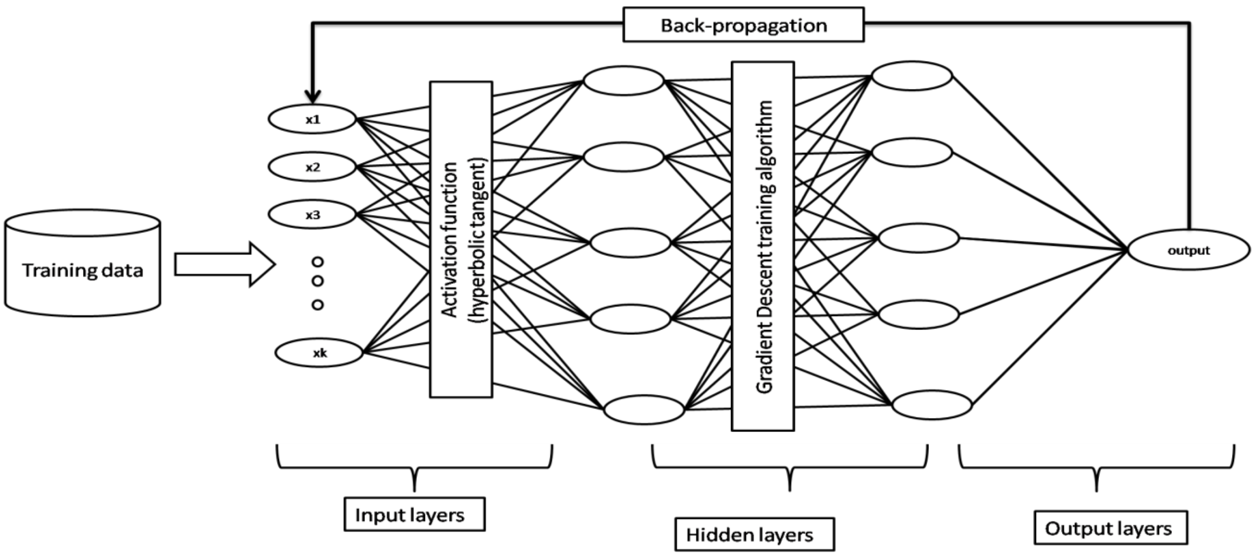

Figure 3: Model of the BNN training

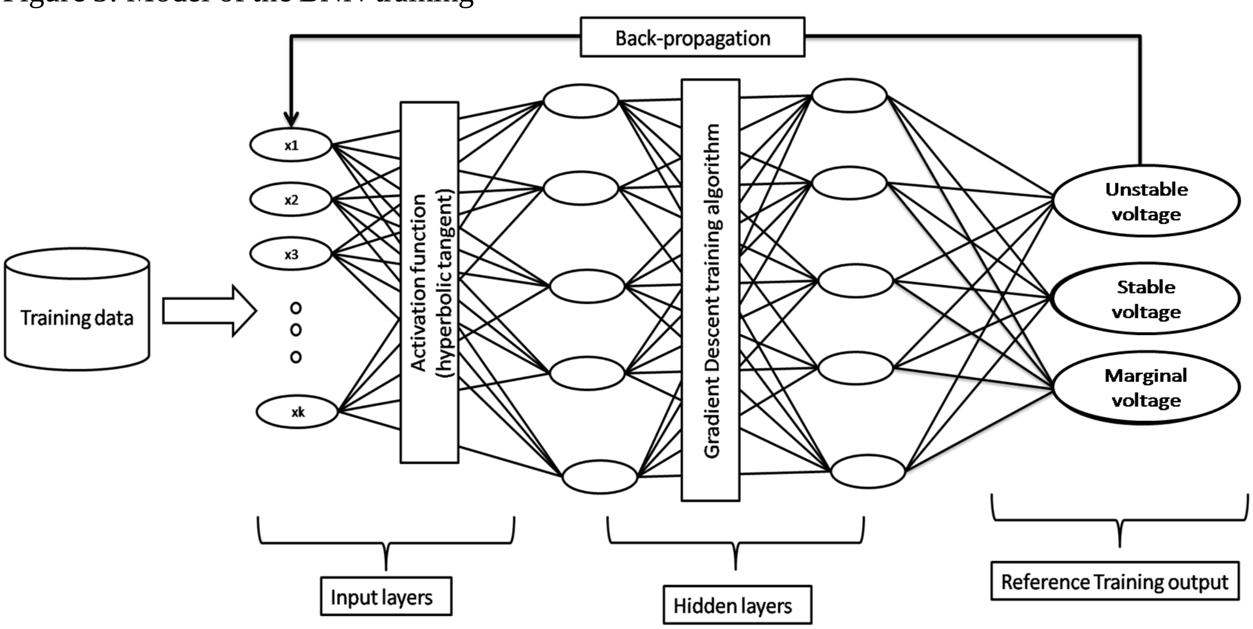

Figure 4: Model of the Power Flow Regression System

The figure 3 presented the model of the BNN training. From the training process the data loaded to the BNN was automatically divided into training, test and validation sets in the ratio of 80:10:10 and then trained. During the training process the gradient descent algorithm adopted from Alexander (2020) was used to adjust the neurons activated and then used Mean Square Error (MSE), Regression (R) and fivefold cross validation tool embedded in the neural application system to evaluate the training performance. The performance was check at epoch intervals until the neurons have learnt the load flow data and the load flow regression model was generated as figure 4. The architectural presented the regression model of the load flow developed with the BNN. The model served as the based for the decision making of the ILFCS which will be developed shortly. The model showed how the load flow parameters were learnt by the BNN using the training algorithm to generate the respective reference models for the stable, marginal and unstable per unit.

4.4 THE INTELLIGENT LOAD FLOW CONTROL SYSTEM (ILFCS)

Power system control requires the identification and balancing of nonlinear parameters attributes to the network which changes due to load and generator behaviors. The two main factors which were controlled were the stable unstable voltage per unit and stable voltage per unit. The power imbalance due to excess reactive power or active power are dependent on the voltage stability margin, hence the control of voltage stability will control the power imbalance and likewise frequency. Today, many control measured are already in place at the transmission sub-stations such as the flexible AC transmission system for power flow control, shunt capacitor bank for power factor corrections among others, however these systems are by default not dynamic enough to detect all changes in the load flow. They only trigger when the power reactive or active power exceeds certain tolerance limits, secondly, they have a probability of failure and often collapse due to poor maintenance culture and hence leaving the quality of transmitted power very poor and the network vulnerable to major problems. There is need for redundant control systems which collected data from the load flow and make sense out of it, by detecting changes in the load flow and take control measures. To achieve this, a simple rule-based optimization algorithm which reads the parameters based on the load flow model in Newton Raphson Load Flow Model was used to read the voltage stability margin on the grid and then take control measured via alarm to notify users of the arising problems and then take precautions measures. The flowchart of the control algorithm is presented in the figure 5;

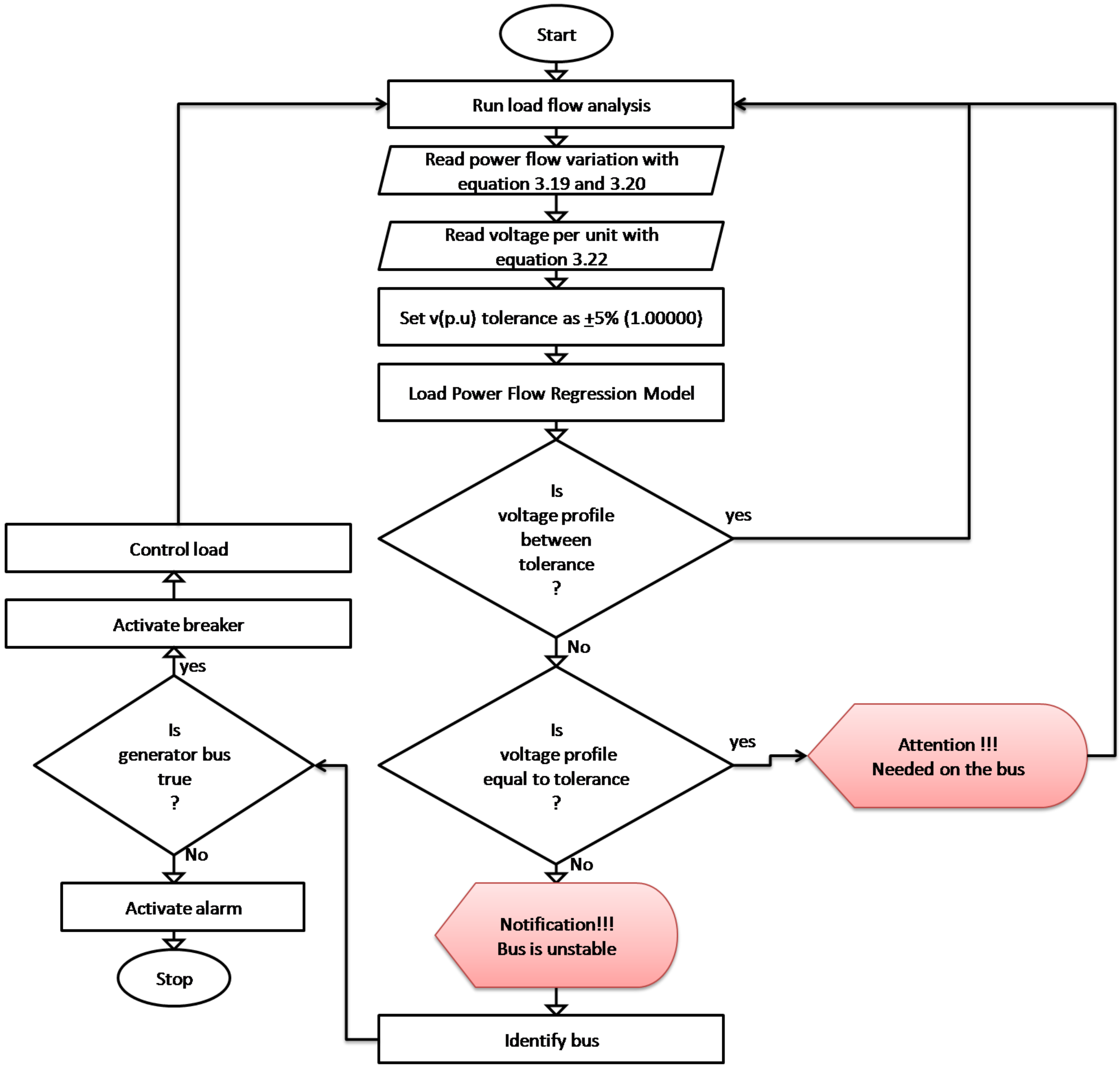

Figure 5: Flow chart of the ILFCS

5.1 System Integration (Intelligent VPP Model)

Having successfully developed the PFRM in figure 5 and the ILFCS in the figure 6, the two models were used to develop the intelligent VPP system proposed. The idea is to use the PFRM as the knowledge based on the VPP and then use the ILFCS as the control system. To achieve this, the algorithm1 which is the ILFCS was used to reprogram the VPP system and develop and intelligent VPP as shown in the figure 6;

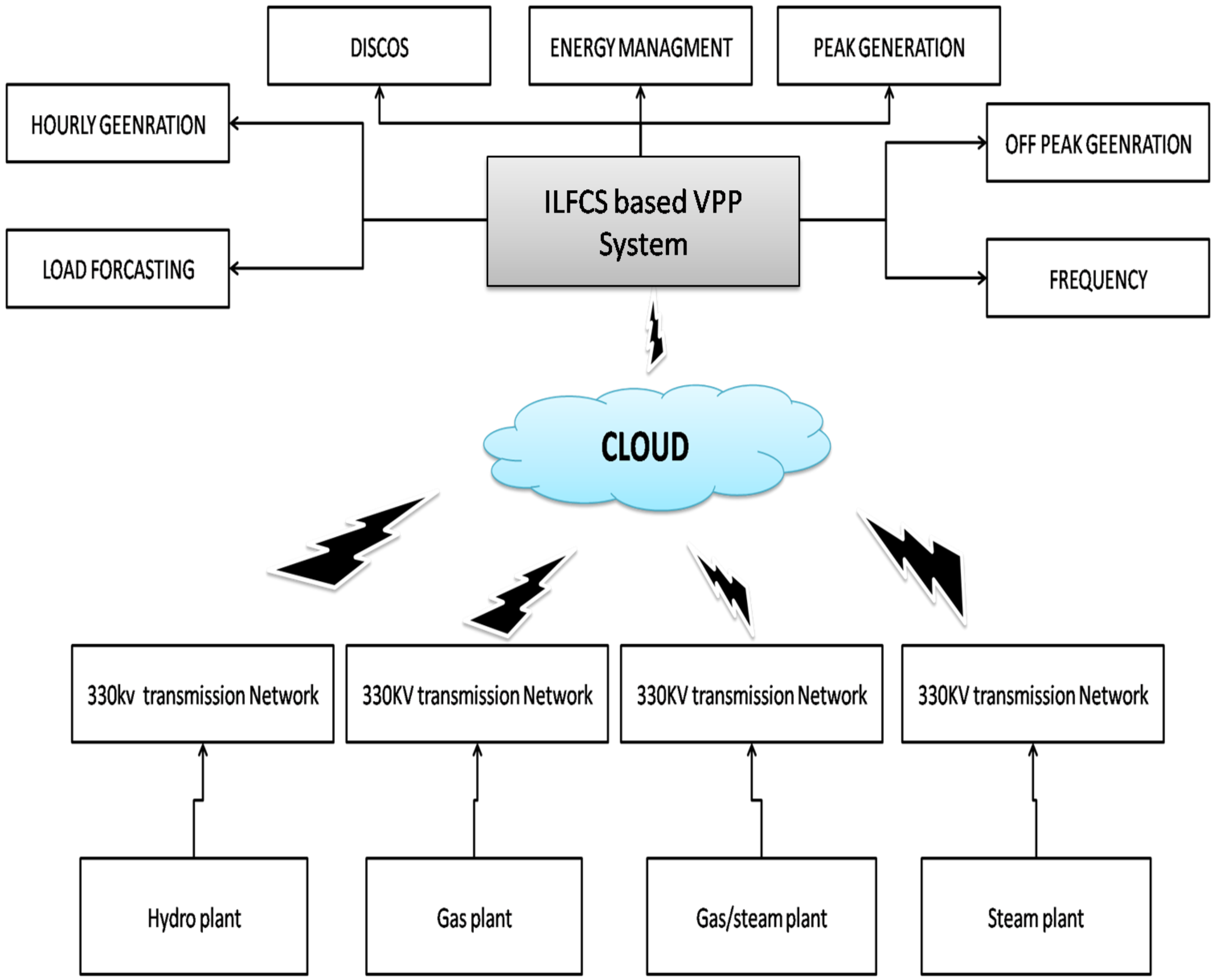

Figure 6: Model of the Intelligent VPP

5. SYSTEM IMPLEMENTATION

The system was implemented with neural network application software and MATLAB. The neural network app was used to develop the PFRM. This was achieved loading the data collected into the platform regression section and then configure the BNN with specifications. Gradient descent algorithm was selected on the app and then used to train the BNN to generate the ILFCS. These was converted to script on the MATLAB platform and then used to develop the intelligent VPP.

6. RESULT OF THE PFRM

The PFRM was developed using the neural network training tool. To evaluate the performance, the MSE and R were engaged. The MSE was used to measure the amount of error which occurred during the training process of the BNN; the result of the MSE was presented in figure 7;

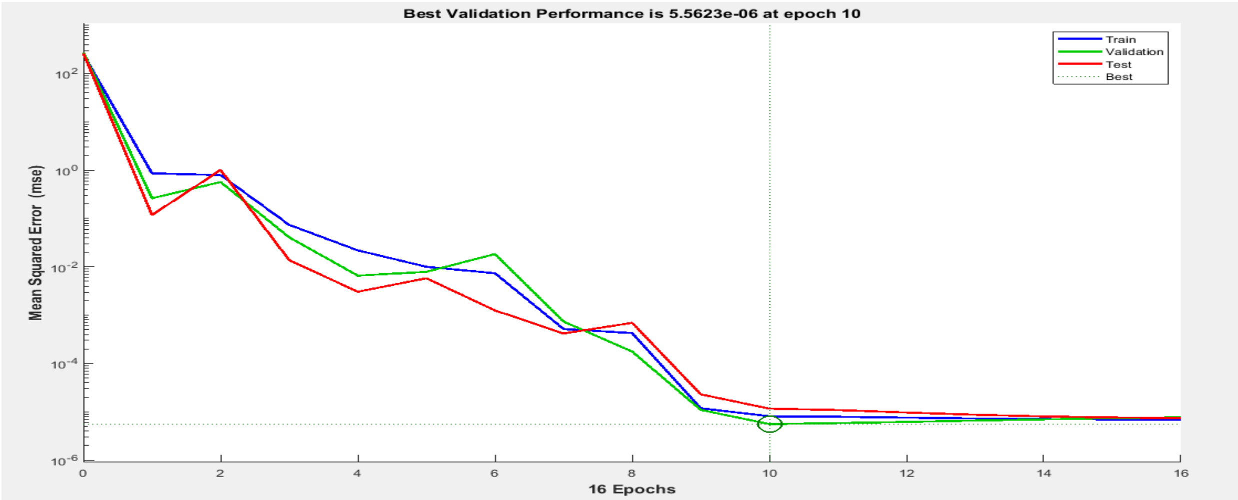

Figure 7: MSE performance of the PFRM

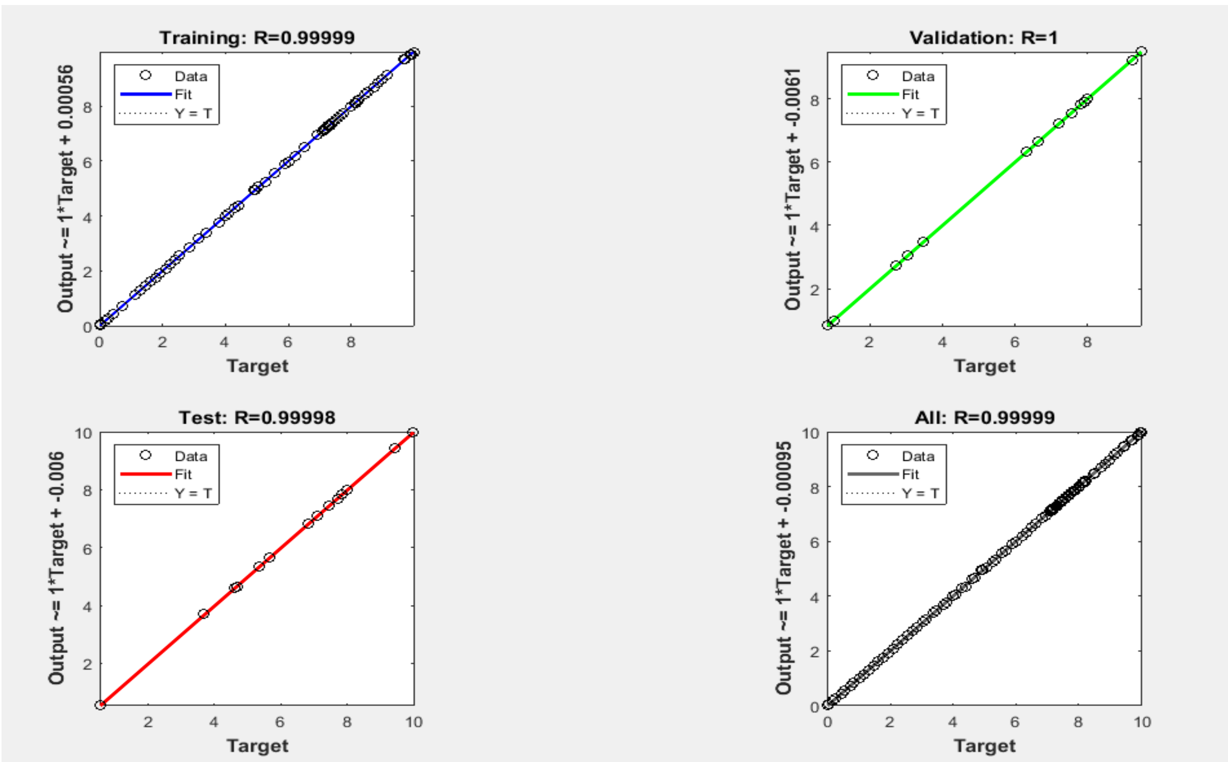

Figure 8: The regression result of the PFRM

From the figure 8, the performance of the MSE was evaluated and reported. The result showed that the MSE performance achieved the best validation at epoch 10 and MSE value of 5.623e-06Mu. The implication of the result showed that the BNN correctly learn the load flow patterns so as to detect abnormally on the grid network. Furthermore, the MSE result achieved was approximately zero which implied that the training achieved tolerable error value which is good. The next result discussed the performance of the R. The R was used to check the ability of the PFRM to detect abnormally arising on the bus from the load or generator side. The R used the test set to check if the PFRM can detect instability on the bus correctly with the aim of achieving

R value equal or approximately 1. Thus implying correct regression performance. The figure 9 presented the performance of the PFRM in terms of detecting time series abnormally on the grid. The result showed that the average R achieved using the training, test and validation set is 0.9999. The implication of the result showed that the BNN was able to detect abnormally on the 36 bus of the 330KV transmission network. This was because the output of the load flow was feedback to the input of the neural network to maintain continuous training and learning of the grid behavior which the reflection was showed in the regression result presented in this section.

7. RESULT OF THE INTELLIGENT VPP

Having tested the performance of the PFRM model developed and integrated with the ILFCS to model the intelligent VPP, the performance when used to monitor the 330KV transmission network as presented in figure 10;

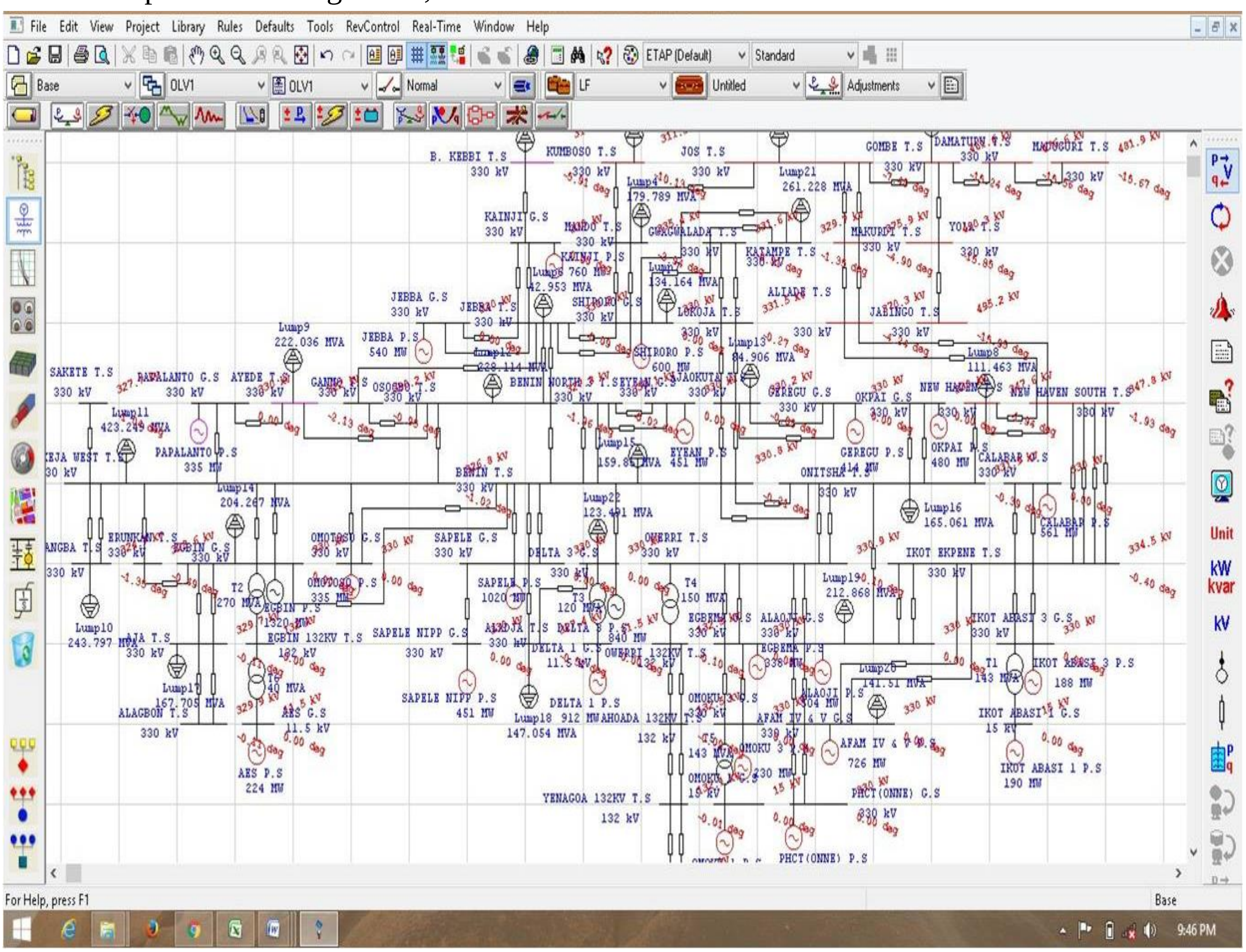

Figure 10: The load flow analysis

The figure 10 presented the load flow analysis used to read the bus and transmission line attitude. This was achieved based on the load flow model and was intelligently used to read the impact of active and reactive power flow variation on the generator and load bus respectively. The resultant stability margin of the grid model was analyzed using voltage profile. From bus voltage collected, the PFRM via the BNN trained and detects the stability status of all the bus on the interconnected network as shown in the figure 11;

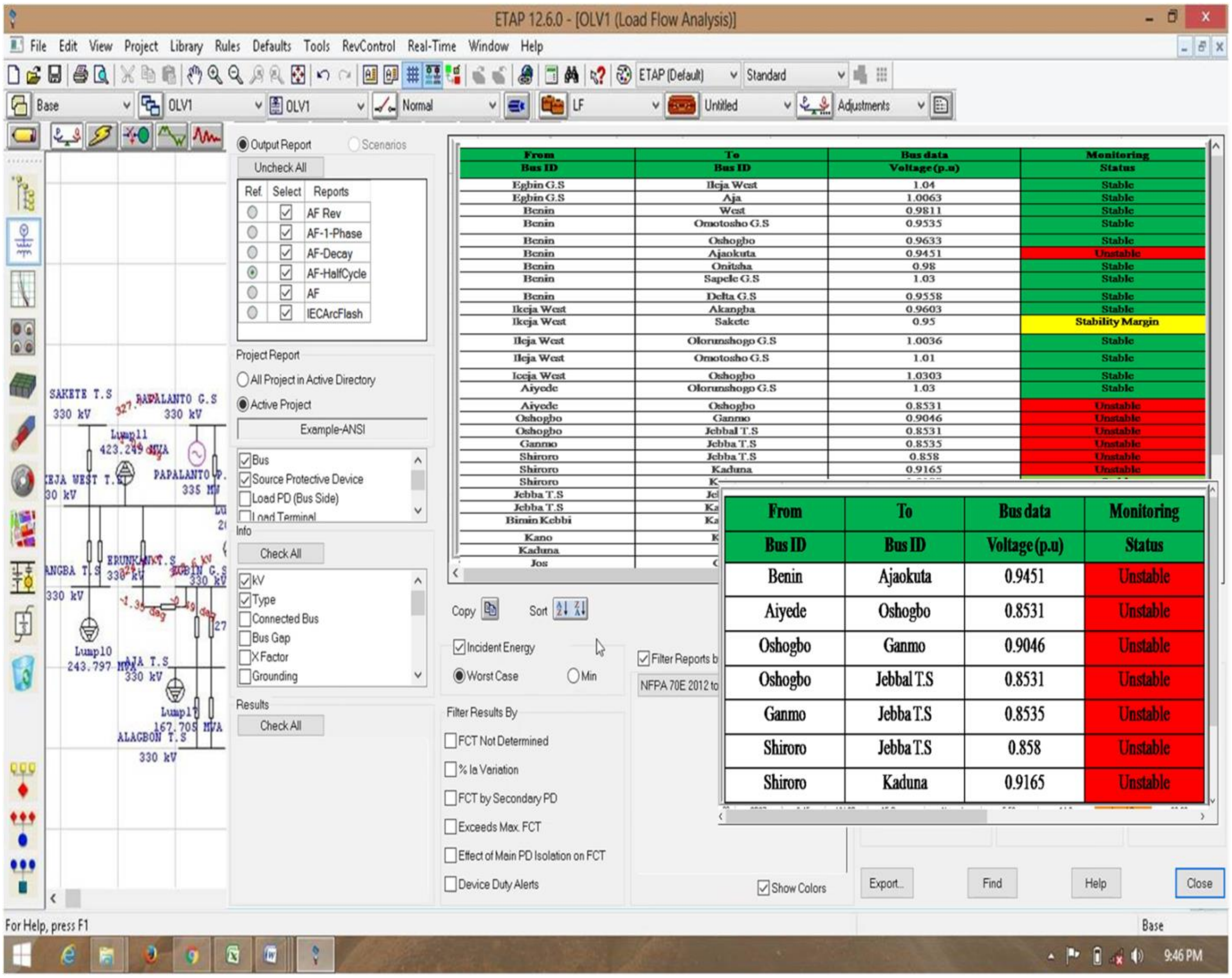

Figure 11: The result of the ILFCS

The figure 11 presented the performance of the ILFCS. The system used the PFRM to train and detect the status of the bus. From the load flow analysis, the voltage stability was identified by the PFRM and then train to detect the status of all the bus on the grid as reported in the table 1;

Table 1: Performance of the VPP intelligent monitoring of the Grid

From	To	Bus data	Monitoring
Bus ID	**Bus ID**	**Voltage (p.u)**	**Status**
Egbin G.S	Ileja West	1.0400	Stable
Egbin G.S	Aja	1.0063	Stable
Benin	West	0.9811	Stable
Benin	Omotosho G.S	0.9535	Stable
Benin	Oshogbo	0.9633	Stable
Ikeja West	Sakete	0.9500	Stability Margin
Aiyede	Oshogbo	1.0036	Stable
Oshogbo	Ganmo	1.0100	Stable
Iceja West	Oshogbo	1.0303	Stable

Oshogbo	Jebbal T.S	1.0300	Stable
Ileja West	Olorunshogo G.S	0.8531	Unstable
Ileja West	Omotosho G.S	0.9046	Unstable
Aiyede	Olorunshogo G.S	0.8531	Unstable
Jebba T.S	Jebba G.S	0.8535	Unstable
Jebba T.S	Kainji G.S	0.858	Unstable
Benin	Ajaokuta	0.9165	Unstable
Shiroro	Katampe	1.0199	Stable
Ganmo	Jebba T.S	1.0300	Stable
Shiroro	Jebba T.S	1.0059	Stable
Shiroro	Kaduna	1.0145	Stable
Kano	Kaduna	0.9653	Stable
Kaduna	Jos	1.0300	Stable
Jos	Gombe	1.0300	Stable
Egbin G.S	Ileja West	1.0300	Stable
Egbin G.S	Aja	1.0300	Stable
Benin	West	1.0356	Stable
Benin	Omotosho G.S	1.0400	Stable
Benin	Oshogbo	1.0063	Stable
Benin	Ajaokuta	0.9811	Stable
Benin	Onitsha	0.9535	Stable
Benin	Sapele G.S	0.9633	Stable

From the table 1, it was observed that the PFRM developed with the BNN was used to train the incoming from the load flow and then based on the NERC standard for bus analysis, identifies the bus status. This was used to monitor the load flow on the grid to detect instability. The ILFCS used this PFRM to detect bus between the specified tolerance values as the stable bus, those with voltage profile equal the tolerance level as bus on their stability margin, while the bus which do not satisfy the tolerance value as unstable bus. After the monitoring o the load flow and bus performance, decisions were made by the ILFCS to control the unstable ones and those at their stability limit as shown in the control result in table 2;

Table 2: Results of the VPP intelligent Control of the grid instability

From	To	Bus data	Control active
Bus ID	**Bus ID**	**Voltage (p.u)**	**Status**
Egbin G.S	Ileja West	1.04	Stable
Egbin G.S	Aja	1.0063	Stable
Benin	West	0.9811	Stable
Benin	Omotosho G.S	0.9535	Stable

Benin	Oshogbo	0.9633	Stable
Ikeja West	Sakete	1	Stable
Aiyede	Oshogbo	0.989	Stable
Oshogbo	Ganmo	1.03	Stable
Iceja West	Oshogbo	0.9558	Stable
Oshogbo	Jebbal T.S	0.9603	Stable
Ileja West	Olorunshogo G.S	1	Stable
Ileja West	Omotosho G.S	1.0036	Stable
Aiyede	Olorunshogo G.S	1.01	Stable
Jebba T.S	Jebba G.S	1.0303	Stable
Jebba T.S	Kainji G.S	1.03	Stable
Benin	Ajaokuta	1	Stable
Shiroro	Katampe	1	Stable
Ganmo	Jebba T.S	1	Stable
Shiroro	Jebba T.S	1	Stable
Shiroro	Kaduna	1	Stable
Kano	Kaduna	0.989	Stable
Kaduna	Jos	1.0199	Stable
Jos	Gombe	1.03	Stable
Egbin G.S	Ileja West	1.0059	Stable
Egbin G.S	Aja	1.0145	Stable
Benin	West	0.9653	Stable
Benin	Omotosho G.S	1.03	Stable
Benin	Oshogbo	1.03	Stable
Benin	Ajaokuta	1.03	Stable
Benin	Onitsha	1.03	Stable
Benin	Sapele G.S	1.0356	Stable
Egbin G.S	Ileja West	1.04	Stable
Egbin G.S	Aja	1.0063	Stable
Benin	West	0.9811	Stable
Benin	Omotosho G.S	0.9535	Stable
Benin	Oshogbo	0.9633	Stable

The table 2 presented the performance of the ILFCS. The result showed how the intelligent VPP used the ILFCS to control the problems on the 330KV transmission network. This was achieved by the identification of the generator bus, which their instability was due to over load from the transmission end and control the load from the circuit breakers situated at the control centre. The other bus which are on their stability limit was also controlled via disconnect of the load to maintain balance on the grid. Other control measure employed is the use of alarm notification to signal abnormally on the grid and also the use of colour changes on the control status to signal abnormally or normal grid behaviour.

8. CONCLUSION AND RECOMMENDATIONS

This paper has successfully presented the modeling of an intelligent virtual power plant for optimal energy network management and control using machine learning technique. The aim is to present a system which can collect data from the grid, interpret it to make control decisions which improved quality of service on the Nigerian 36 bus, 330KV interconnected transmission network. The methodology employed is the experimental method while the research methodology used is the waterfall model. The methods used are data collection, data processing, development of the PFRM, ILFCS, IVPP. These methods were modelled with structural approach and then implemented with MATLAB. The result showed that the IVPP was able to intelligently monitor and control the load flow on the grid.

8.1 Recommendation

Having completed this research and tested the performance, the following were recommended;

i. The IVPP should be deployed at other sub-sections of the transmission network control centres for monitoring of the 132/33KV transmission lines
ii. The IVPP should be employed by the distribution companies for monitoring and control
iii. The IVPP should be employed at the NCC Oshogbo for the national grid supervision and control

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