IMPROVING THE REAL TIME SUPERVISORY NETWORK PERFORMANCE IN 330KV TRANSMISSION STATION USING INTELLIGENT PHASOR MONITORING AND CONTROL SCHEME

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Abstract

This paper focuses on improving the performance of the SCADA network in a 330/132kV transmission station by employing a phasor-based intelligent monitoring scheme. The study assesses the characteristics of the Alaoji SCADA system, which is designed with a Remote Telemetry Unit (RTU), and identifies challenges related to data synchronization and collection delays. To address these issues, the proposed methodology involves data collection from the Alaoji 330/33kV station, data processing using a three-phase shunt active filter, Phasor Measurement Unit (PMU), artificial neural network training, and classification. The system design incorporates a structural approach to model the 330/132kV substation, phasor measurement unit, feed-forward neural network, and the Intelligent Load Flow Sampling Algorithm (LFSA). The implementation of the system is carried out using the Simulink platform, and its performance is evaluated using the tenfold cross-validation technique. The results demonstrate that the new LFSA achieves data collection and transmission within 14.3ms, a significant improvement compared to the characterized result of 540ms. The mean square error is reduced to 0.053288Mu, indicating high accuracy as it approaches zero, with an overall accuracy of 98.3%. Integration of the system at the Alaoji 330/132kV transmission station enables high-quality and integrity data collection, thereby enhancing decision-making processes within the station.

Keywords: Phasor Measurement Unit; Transmission; SCADA; Remote Telemetry Unit; Load flow sampling algorithm; Artificial Neural Network

1. INTRODUCTION

Power systems are classified into three main sections: generating stations, transmission, and distribution stations. These sections are interconnected and responsible for various activities involved in producing and delivering power to end-users for various applications. The generating station generates power from natural or other sources, and its capacity is increased using step-up transformers in substations. The power is then transmitted through the transmission systems to the grid. The distribution system brings down the transmitted power to a level compatible with the user's load for domestic and industrial applications. Currently, these three sections of the power system face numerous challenges, primarily due to the poor architectural state of the Nigerian power system network. According to Tsado et al. (2015), Nigeria's power sector is in a dire state, further complicated by transmission constraints and limitations. These issues include instabilities, system collapses, recurring blackouts, voltage sags, slow expansion of the transmission grid, poor transfer capability and capacity, as well as power capacity shortfalls and line outages.

Over time, the traditional approach to collecting data and studying the behavior of the power system has involved the use of remote monitoring through Supervisory Control and Data Acquisition (SCADA) systems. These SCADA systems collect data from power system equipment located in stations, remote areas, plants, or any other relevant location, via Remote Terminal Units (RTUs). The collected data is then transmitted to the control center for analysis and decision-making. Remote Terminal Units (RTUs) are microprocessor-based devices that are connected to sensors, transmitters, or process equipment for remote telemetry and control purposes. RTUs have various applications, including oil and gas remote instrumentation monitoring, networks of remote pump stations, power system monitoring, environmental monitoring systems, air traffic equipment, and more. However, a significant challenge with RTUs is time synchronization or precision timing. Precise timing is crucial for making accurate decisions and synchronizing data points in smart grid monitoring. Meeting the millisecond application requirements of the grid information system network for time synchronism and situational awareness is essential for operators to make reliable decisions both on and off the field.

In the Nigerian power system, RTUs are currently mounted in on-grid locations due to their ruggedness and ability to withstand harsh atmospheric conditions for data collection and grid monitoring. However, there is a time difference of approximately 540ms (Bowen et al., 2005) between the RTU time and real-time. This time delay significantly impacts the reliability of the collected data and decision-making. Therefore, there is a need for the development and utilization of a real-time data collection system for smart grid monitoring. To achieve real-time data acquisition in the SCADA system, this study proposes the use of Phasor Measurement Units (PMUs). PMUs are devices that were introduced in the early 1980s and have since become a mature technology with numerous applications currently under development worldwide. The occurrence of major blackouts in many power systems globally has led to increased interest in the large-scale implementation of Wide-Area Measurement Systems (WAMS) using PMUs and Phasor Data Concentrators (PDCs) in a hierarchical structure (Martinez et al., 2015). However, PMUs face challenges regarding reliability (poor accuracy) and sampling rate. This study proposes addressing these issues using artificial intelligence techniques and deploying the improved PMUs to enhance the ALAOJI 330KV transmission station.

2. LITERATURE REVIEW

Emmanuel et al. (2016) conducted a study on enhancing electric power transmission. The research focused on assessing the performance of the 330 and 132KV transmission network through descriptive analysis. They recommended the use of a real-time monitoring device for data acquisition and control purposes. Luo et al. (2018) investigated the fault location in transmission networks using sparse field measurements, simulation data, and genetic algorithms. Their research involved developing an algorithm that utilized sparse field and simulated data for real-time fault detection in transmission lines with the aid of genetic algorithms. Despite its success, this technique can be further improved by incorporating recent A.I. algorithms. Zhang et al. (2015) presented a study on enhancing real-time fault analysis and validating relay operation to prevent or mitigate cascading blackouts. The research involved collecting data on relay behavior in protection zones using Remote Telemetry Units (RTUs) and analyzing their behavior with the assistance of SCADA. However, the response time of the RTU was observed to have significant delays. Qurat et al. (2015) conducted a study on implementing SCADA for multiple telemetry units while utilizing GSM for communication. The research aimed to design a GSM-based SCADA system for remote monitoring and feedback, incorporating multiple telemetry units and GSM technology. However, the telemetry device used in their study did not provide real-time data collection capabilities. Martinez (2015) presented a study on the phasor data requirements for real-time wide area monitoring, control, and protection applications. The study involved collecting real-time data from circuit breakers and relays using Phasor Measurement Units (PMUs) and analyzing it through SCADA. This technique is intended to be implemented at the ALAOJI power station.

3. METHODOLOGY

The methodology employed for the development of the new system is the Rapid application development methodology which accommodates the use of structural and mathematical method of modeling for the development of new systems in engineering. The method collected data of Alaoji transmission station and used to develop an artificial (feed forward) neural network algorithm. The algorithm was then used to improve the model of PMU to develop the proposed intelligent PMU system which was deployed for improved SCADA design.

The Network Under Study

The model of the alaoji 330/132kv SCADA network is hereby presented using structural method. The incoming from the Alaoji 330KV bus are step down to 132KV and then transmitted to the Afam 1, Afam 2, Owerrir 1, Owerri 2, Aba 1, Aba 2, Umuahia 1 and Umuahia 2 132/33KV transmission feeders respectively as shown in the figure 1;

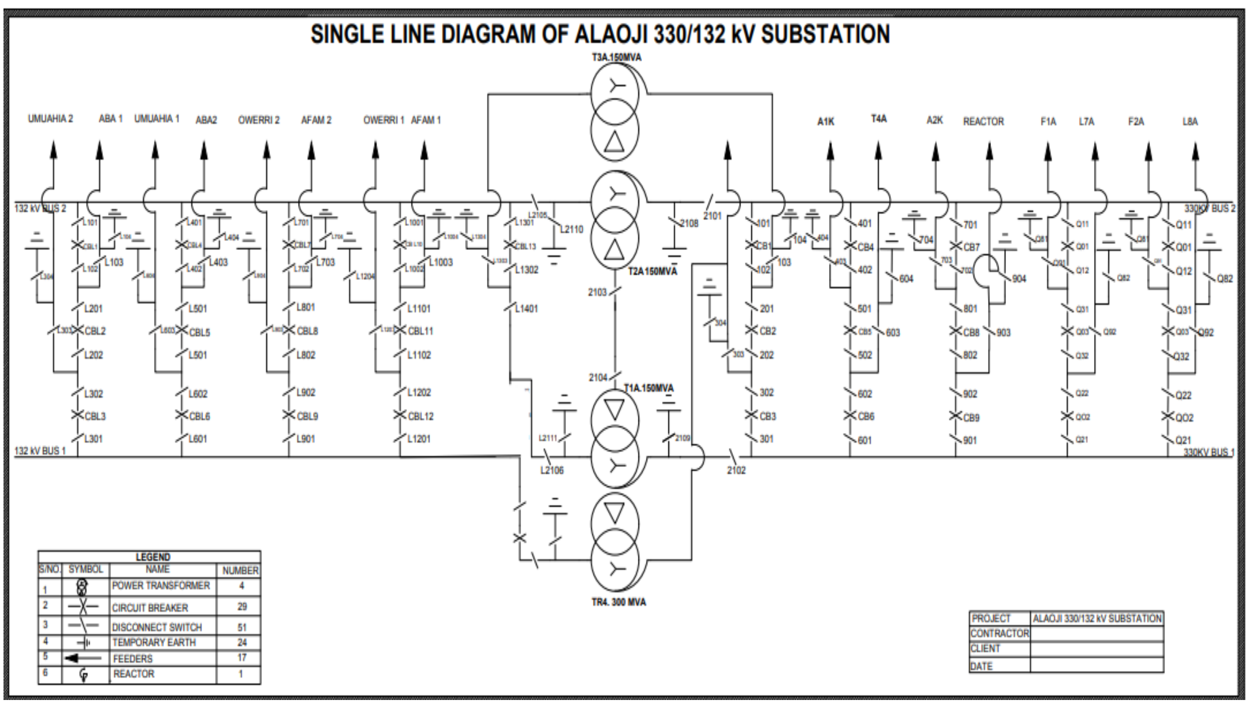

Figure 1: Single line diagram of the Alaoji 330/132KV substation (Source: Alaoji station)

The SCADA system measurement set up at alaojistatation is monitoring Afam 1, Afam 2, Owerrir 1, Owerri 2, Aba 1, Aba 2, Umuahia 1 and Umuahia 2 132/33KV transmission feeders respectively.

The Phasor Measurement Unit System

From the results of the related literatures, it was uncovered that the RTU suffers many limitations like delay response time and data synchronization time. The PMU was introduced to address this problem as shown in the model of figure 2;

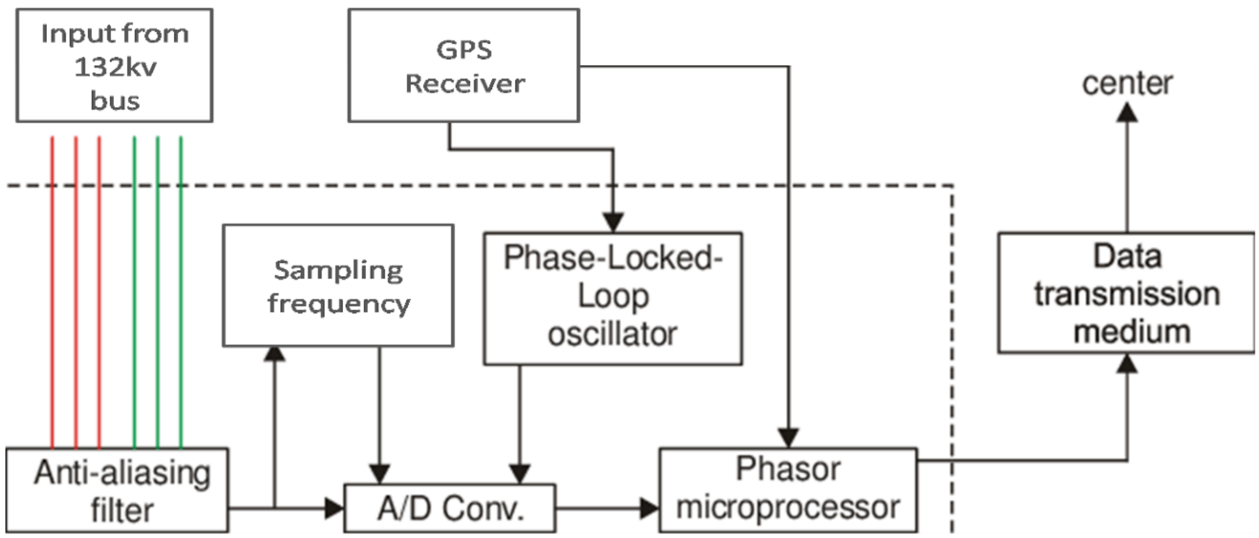

Figure 2: Model of the PMU

In Figure 2, the Phasor Measurement Unit (PMU) is composed of several components that enable its functionality:

1. GPS Receiver: The GPS receiver is a crucial component of the PMU. It receives signals from a global positioning system (GPS) consisting of 24 satellites operating synchronously in 6 orbits. These satellites provide precise location and time information in Universal Time Coordinate (UTC) format. By integrating the GPS receiver with the PMU, the collected data can be accurately time stamped, ensuring time synchronization for phasor-based systems.

2. Analog to Digital Converter (ADC): The ADC is responsible for converting the analog signals, specifically the current and voltage signals from the substation transformer, into digital format. This conversion enables the subsequent processing and analysis of the phasor measurements.

3. Filters: The PMU utilizes filters to process the sampled data obtained from the ADC. These filters operate based on the Nyquist-Shannon sampling theorem, ensuring that the sampled signals are processed using a sampling frequency that is at least twice the frequency of the original phasor signal. This process helps eliminate any aliasing or distortion in the data, ensuring accurate representation of the phasor quantities.

4. Microprocessor: The microprocessor is the core processing unit of the PMU. It performs various computations and algorithms to analyze the phasor measurements and extract relevant information. The microprocessor plays a vital role in real-time data processing and generating synchronized phasor measurements.

5. Software Defined Radio (SDR): The SDR facilitates the transmission of data from the PMU to the designated receiving system. It enables wireless communication and ensures the reliable transfer of phasor measurement data.

6. Phase Locked Oscillator (PLO): The PLO is responsible for locking the pulse signal obtained from the GPS. It utilizes a phase-locked loop and a sampling clock (typically 12 per cycle) based on the fundamental sampling frequency. This synchronization ensures accurate alignment and timing of the received signals, further enhancing the reliability of the PMU's phasor measurements.

The integration of these components in the PMU system allows for precise phasor measurements and accurate synchronization of data, enabling real-time monitoring and analysis of power systems. The references provided (Chandragupta and Ramkumar, 2014) offer more detailed information on the operation and functionality of the PMU and its individual components.

3.1 To Develop an Intelligent Control System

From the model of the PMU, the control system was developed with proportional integral derivative (PID) controller. The limitation of the PMU with this PID is the poor quality of data been collected. This is because the load flow is accompanied with other noisy information like flickers, harmonics, etc. these attributes when collected with the bus data makes the quality ofdata lack integrity. This problem was addressed in this paper using an artificial neural network which was trained with the data required to be collect to generate a load flow control system which was incorporated with the PMU.

4. THE ARTIFICIAL NEURAL NETWORK

The Feed Forward Neural Network (FFNN) algorithm used in the research was adopted from Cletus and Eke (2022). The FFNN was developed with attributes such as interconnected neurons which have weight, bias, activation function and training algorithm. The model of the FFNN was presented in the figure 3;

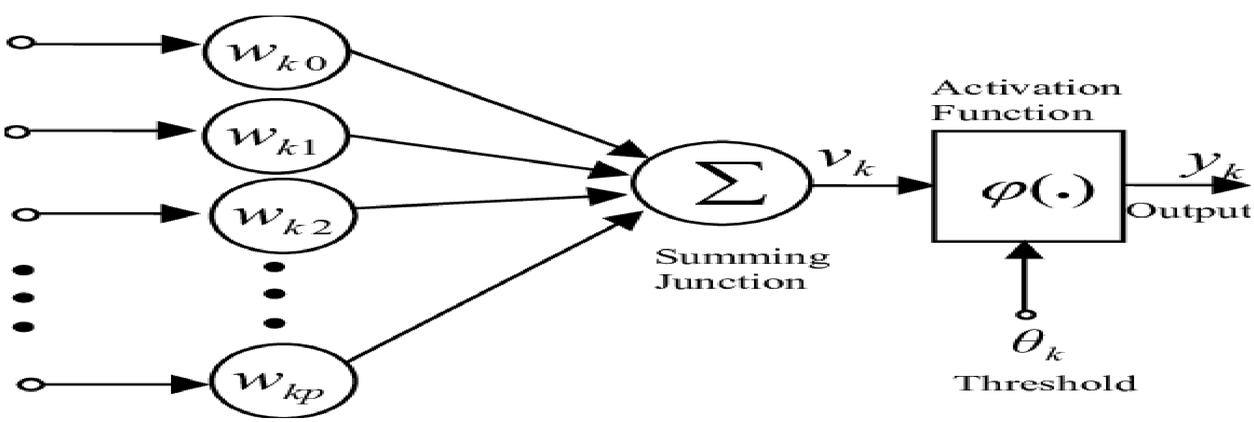

Figure 3: Architectural model of the FNN

Where w is w_{ko} is the bias, w_{kp} is the weight, v_k is the summation of neuron, φ is the tansig activation function used, y_k is the output. The number o the input was determined based on the bus data collected from the substation.

3.6.3 Training of the FFNN

To train the FFNN, the data collected were loaded to the FFNN input neurons and then a back propagation training algorithm as presented in the Algorithm 1 was used to train the neurons. The training process adjusted the neurons weights to learn the features of the 132/33KV bus data for the 8 feeders connected to the Alaoji 330/132KV station.

3.6.4 Back Propagation (Algorithm 1)

1. Start
2. Import Dataset
3. Select feature variables from the dataset
4. Initialize weights and bias functions with suitable thresholds
5. Iterate over the dataset to update weights and biases
6. Check epoch performance at regular intervals (e.g., every 10 steps)
7. If training is satisfactory (performance meets desired criteria)
8. Stop training
9. Generate the reference phasor model based on the trained neural network
10. Else, continue training until the desired epoch is reached
11. Repeat steps 5 to 10 iteratively
12. End

The training of the FFNN was performed to learn the neurons of the features of the substations. Before the training began, the data collected were separated into the ratio of 80:10:10 or training, test and validation sets. The training data were used by the FNN to learn the features of the load flow. The test data was used to check its ability to collect correct data from the substations without noise while the validation data was used to validate the result of the training process based on five old cross validation technique. All these operations were performed using the neural network application software in Simulink 2021a. After the training was completed the algorithm of the intelligent load flow sampling system was generated as algorithm 2.

4.1 Neural network based PMU Load Flow Sampling System (ALGORITHM 2)

1. Start
2. Load data
3. Split data into training, test, and validation sets
4. Configure an intelligent PMU performance neural network
5. Activate the training algorithm (back-propagation)
6. Train the neural network using the training set
7. Test the performance of the trained neural network using the test set
8. Evaluate the performance of the neural network using suitable metrics (e.g., accuracy, precision, recall)
9. Check if the validation performance meets the desired criteria
10. If the validation performance is satisfactory, proceed to the next step
11. Generate the intelligent PMU performance algorithm based on the trained neural network
12. Else, go back to step 5 and continue training the neural network until the validation performance is satisfactory
13. Apply the intelligent PMU performance algorithm in real-time operations
14. Monitor and assess the performance of the PMU system using appropriate evaluation tools and techniques
15. Continuously update and refine the intelligent PMU performance algorithm based on new data and system requirements

16. End

4.2 Development of the Intelligent Phasor Monitoring and Control Scheme

To develop the intelligent phasor monitoring and control scheme, the intelligent load flow sampling algorithm was incorporated with the PMU model as shown in the figure 4 to develop the intelligent phasor monitoring and control scheme.

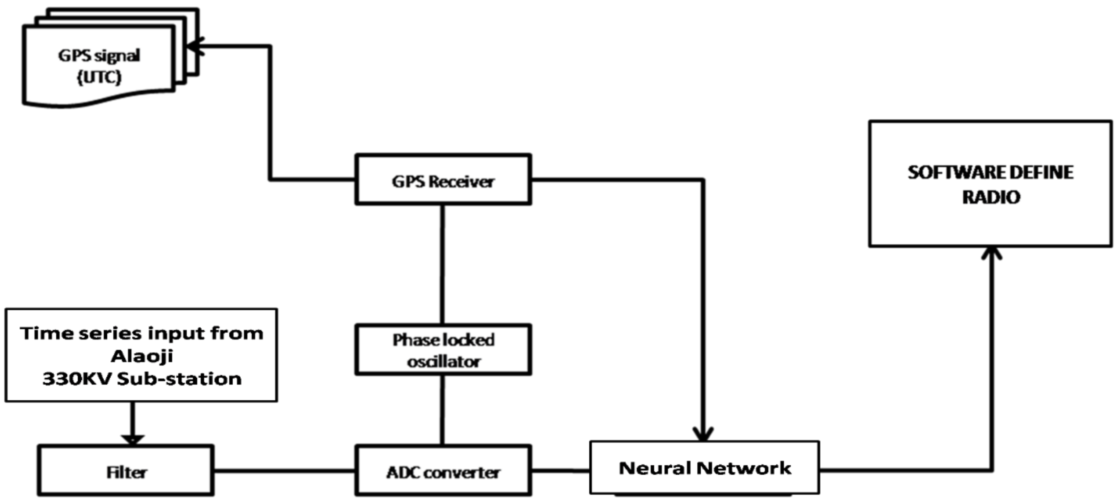

Figure 4: The intelligent phasor monitoring and control scheme

The figure presented in Figure 4 represents the neuro PMU system developed using a neural network. In this system, the intelligent phasor monitoring and control scheme is implemented using the intelligent load flow sampling algorithm (ILFSA) in conjunction with the PMU model.

The neuro PMU operates as follows:

1. Data Collection: Data from the PMU filters is collected, which includes synchronized GPS information and other relevant measurements.

2. Intelligent Load Flow Sampling Algorithm (ILFSA): The collected data is processed using the ILFSA, which has been trained with high-quality data from the substation. The ILFSA classifies the attributes of the data based on its training and classification capabilities.

3. Attribute Classification: The trained ILFSA classifies the attributes of the collected data, extracting meaningful information related to power system dynamics, stability, and performance.

4. Transmission to Control Center: The classified attributes are transmitted to the control center for further analysis and decision-making. This allows the control center to have accurate and valuable information for monitoring and controlling the power system.

5. Quality Data Selection: The neuro PMU ensures that only high-quality data, which has been classified and verified by the ILFSA, is selected and transmitted for network analysis. This helps in improving the reliability and accuracy of the monitoring and control system.

By leveraging the neural network-based approach and the ILFSA, the neuro PMU system enhances the capabilities of traditional PMUs by providing intelligent attribute classification and selecting high-quality data for network analysis and control purposes.

5. SYSTEM IMPLEMENTATION

The system was implemented using neural network toolbox, power system toolbox and Simulink. The neural network toolbox was used to integrate the algorithm developed in figure 1 to the conventional PMU model to achieve the new system as shown in the developed model in figure 2. The Simulink implementation is presented in figure 5;

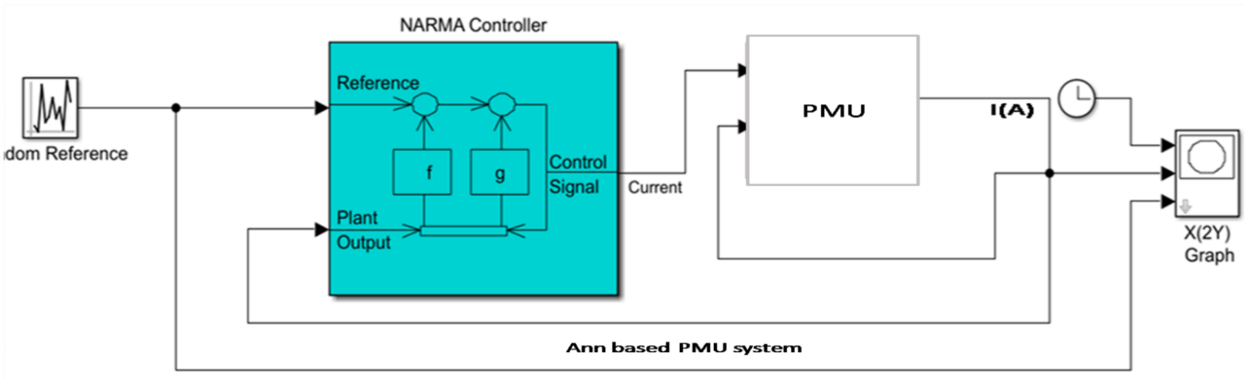

Figure 5: the Simulink model of the intelligent PMU System

The model in figure 5 presented the model of the new PMU developed in the study. The system implementation results of the PMU incorporated with the ILFSA developed with the neural network was presented.

5.1 Performance evaluation

Step response performance to measure the data sampling and delivery time in ms.

$$c(t) = C_{tr}(t) + C_{ss}(t) \quad (1)$$

Where $C_{tr}(t)$the transient is time and $C_{ss}(t)$ is the steady state time. The model in equation 1 was used to measure the step response of the Alaoji SCADA station. To measure the system accuracy, the relationship between the True positive rate and specificity false positive rate was used as in equation 2 and 3;

$$\text{True Positive Rate (TPR)} = \frac{TP}{TP+FN} \quad (2)$$

$$\text{False positive Rate (FPR)} = \frac{TN}{TN+FP} \quad (3)$$

Where TP is true positive, FN is false negative, TN is true negative and FP is false positive. The accuracy of the classifiers was measured using the relationship between equation 2 and 3 as shown in the model of equation 4.

$$\text{Accuracy (ACC)} = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \breve{y}_I)^2 \quad (5)$$

Where n is number of data; y_i is observed value, $\breve{y}_I$ is predicted value

6. RESULTS

To discuss the result of the intelligent PMU developed, the performance of the algorithm used to improve the PMU model was examined using the performance evaluation models from equation 2 to equation 5. The first parameter considered to evaluate the performance of the PMU is the Mean Square Error (MSE) performance in equation 5. The aim here is to check and determine the error rate achieved during the training process. The ideal MSE value for reference is zero, however any result approximately zero is very good and indicated good training performance. The MSE graph is presented in figure 6;

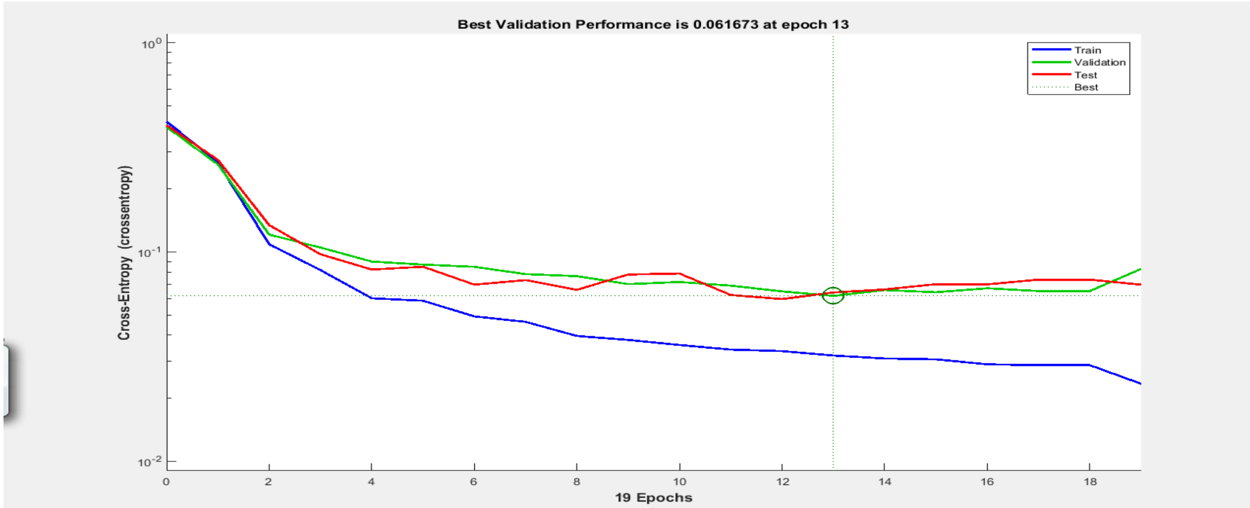

Figure 6: MSE Analysis

The result in figure 6 presented the MSE performance of the intelligent PMU used to improve, the result showed that the MSE value is 0.061673Mu at epoch 13 which is very good. The epoch is the parameter the neural network used to evaluate the performance at each training step and once the best MSE was achieved, the evaluate stops automatically implying that the algorithm have correctly learned the data. The next result presented the regression analysis of the new PMU system using receiver operator characteristics curve which employed TPR and FPR to evaluate the regression performance a system and then compute the overall score as presented in the figure 7;

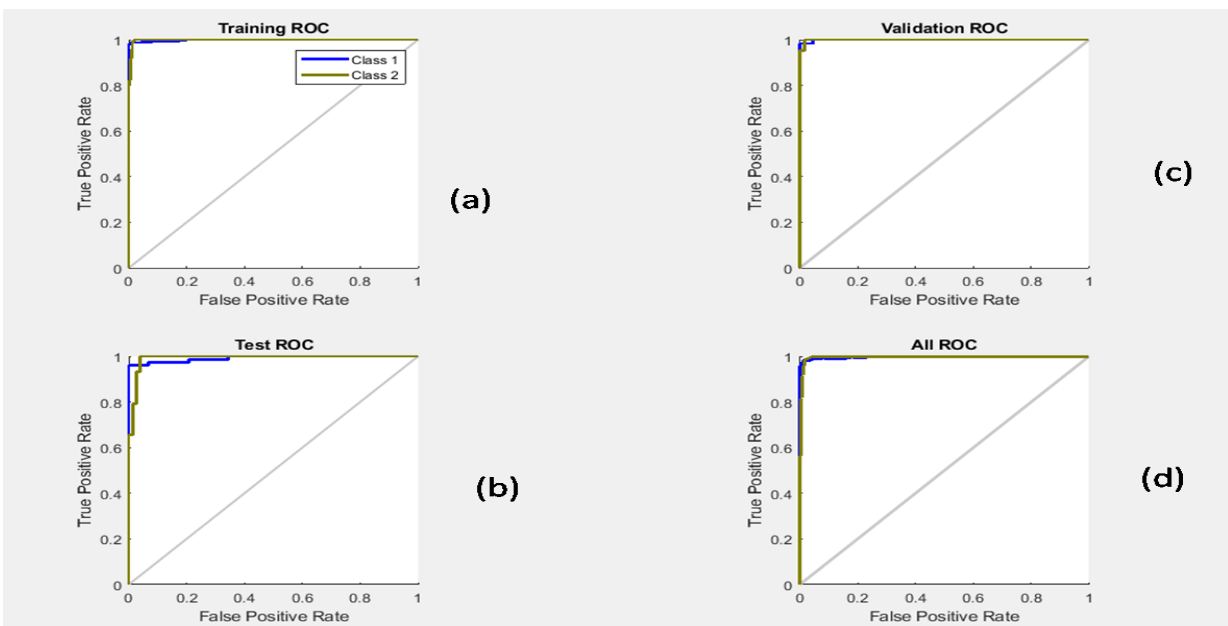

Figure 7: The ROC analysis

The figure 7 presented the ROC performance of the intelligent PMU model developed as shown in figure 1. The result was achieved using the model in equation 2 and 3 to formulate and compute the regression (R) score of the PMU which is a very vital parameter to check system reliability. The result in figure 7 showed R value of 0.983 which is very good as it is very close to the ideal R value which is one. The implication of this result showed that the Intelligent PMU was able to correctly learn the load flow of the Alaoji substation and transmit accurately. To measure how accurate the data received are, the confusion matrix in figure 8 was used.

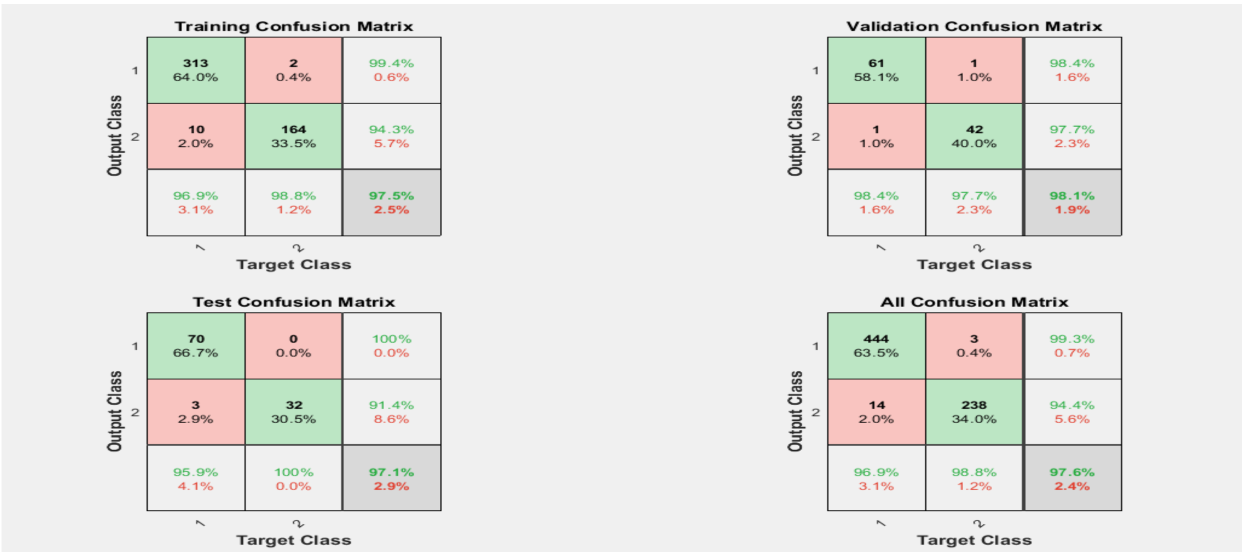

Figure 8: The confusion matrix analyzer

From the figure 8 the performance of the intelligent PMU was measured using the accuracy model in equation 4. The result showed that the accuracy achieved is 97.6% for correct classification of load flow to the software defined radio which transfers to the monitoring center. This overall accuracy was computed using the average of the test, training and validation accuracy as shown in the figure above to compute the overall PMU data sampling accuracy. The next result measured the step response performance of the intelligent PMU developed using the response time model in equation 1 and the result is presented in figure 9;

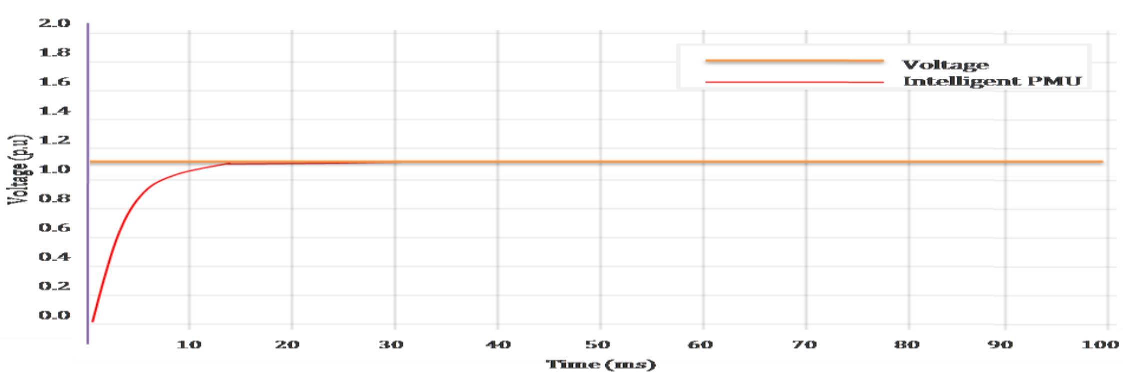

Figure 9: the step response of the intelligent PMU

The figure 9 presented the step response performance of the intelligent PMU system which was sued to evaluate the time of data delivery by the PMU. The delivery time is 14ms which according to (Kopetz, 1997; Kuo and Lee, 2006) which specified that any time below 20ms is real time. The delay however was not from the PMU as it collected data in exact real time, but due to the technical limitations of the software defined radio, the latency of 14ms was induced which is still acceptable.

6.1 System Integration

The neuro PMU system was subjected to system integration testing on the Alaoji 330/132KV transmission network as a case study. The testing involved monitoring the system using SCADA (Supervisory Control and Data Acquisition) and collecting relevant data for analysis. The test results obtained from the neuro PMU system on the Alaoji transmission network were documented and reported in Table 1. The table presents the collected data and corresponding measurements, providing insights into the performance and behavior of the power system. The integration testing of the neuro PMU system on the Alaoji transmission network, along with the results presented in Table 1, demonstrates the system's capability to monitor and analyze the network's dynamics, enabling efficient control and decision-making in real-time operations.

Table 2: performance of the Improved SCADA

Time (hr)	Afam1	Afam 2	Owerri 1	Owerri 2	Umuahia 1	Umuahia 2	Aba 1	Aba 2
1	0.987032	0.949304	0.987032	0.949304	0.987332	0.987032	0.961032	0.987032
2	0.968026	0.986324	0.958026	1.000000	0.958026	0.958026	0.978026	0.958026
3	0.988455	0.987268	0.998455	0.983033	0.998455	1.000000	0.988455	0.949304
4	1.000000	0.978903	1.000000	0.986324	0.984424	0.982444	1.000000	0.995670
5	0.786304	0.988672	0.949304	0.986324	0.746304	0.949304	0.949304	1.000000
6	0.975670	0.987060	0.995670	0.995670	0.995670	0.995670	0.995670	0.983033
7	1.000000	0.986324	1.000000	0.986375	0.983432	0.986324	1.000000	1.000000
8	0.893033	0.681268	0.983033	0.843033	0.843033	0.987268	0.983033	0.991724
9	1.000000	0.988903	0.949304	0.949304	0.949304	0.978903	1.000000	0.997640
10	0.986324	0.986324	0.995670	0.995670	0.995670	0.988672	0.986324	0.986013
11	0.987640	0.987268	1.000000	0.986324	0.965824	0.987060	0.963640	0.949304
12	0.976013	0.978903	0.983033	0.983033	0.983033	0.986013	0.985413	0.995670
13	0.949123	0.988672	0.986324	1.000000	0.949304	0.949304	0.985623	1.000000
14	1.000000	0.987060	0.987268	0.986324	0.995670	0.986324	0.949304	0.983033
15	1.000000	0.986324	0.978903	0.963640	1.000000	0.987268	0.995670	1.000000
16	1.000000	0.987268	0.988672	0.985413	0.983033	0.978903	1.000000	0.986324
17	0.791268	0.681268	0.681268	0.681268	0.681268	0.681268	0.983033	0.987268
18	0.978903	0.988903	0.988903	0.986324	0.988903	0.988903	0.988903	0.978903
19	0.989632	0.980632	0.980632	0.987268	0.980632	0.980632	0.980632	0.988672
20	0.895060	0.891060	0.891060	0.978903	0.891060	0.891060	0.891060	0.987060
21	1.000000	1.000000	1.000000	0.988672	1.000000	1.000000	1.000000	1.000000
22	0.889970	0.699970	0.699970	0.699970	0.699970	0.699970	0.699970	0.699970

23	0.958903	0.988903	0.988903	0.988903	0.988903	0.988903	0.988903	0.988903
24	0.987032	0.949304	0.987032	0.949304	0.987332	0.987032	0.961032	0.987032

The table 2 presented the performance o the data collected from the Alaoji substation with the intelligent PMU developed with FFNN. The result showed the real data of the load flow collected without harmonics and noise for 24 hours. The implication of the result showed that when data was collected from the load flow, the load flow sampling algorithm was used to classify the output, thereby transmitting only quality data to the SCADA.

Comparative SCADA Results with Neuro PLC and without Neuro PLC

The comparative analysis presented in this study focuses on the performance of SCADA with LFSA (Load Flow Sampling Algorithm) and SCADA with RTU (Remote Terminal Unit). The evaluation compares the performance of the 132/33KV bus data collected from the Alaoji 330/132KV transmission station control center using traditional SCADA with RTU and the new data collected using a neuro PMU-based SCADA system over a 24-hour period. The detailed tables used for the comparative analysis can be found in the Appendix. Table 3 specifically compares the Umuahia 1 and 2 buses, considering both the neuro PLC (Programmable Logic Controller) and traditional SCADA with RTU. The analysis reveals noticeable differences between the data collected with RTU and the data obtained with the neuro PMU. These discrepancies can be attributed to the presence of noise and harmonics in the RTU data. Additionally, the poor sampling and delay time of the RTU result in non-real-time data collection, compromising data integrity. Table 4 compares the data from SCADA with and without the neural network PMU for the Aba 1 and 2 132/33KV network. Similarly, Table 5 examines the Owerri 1 and 2 buses, while Table 6 focuses on Afam 1 and 2. The results indicate variations in the voltage profiles of all the buses, with the neuro PMU providing more stable measurements compared to the SCADA system without the neuro PMU. This implies that the neuro PMU enables the collection of more up-to-date data for the Alaoji 132/33KV network, enhancing control stability analysis compared to using SCADA alone. Furthermore, a comparative step response was presented as in figure 10, which compared the response time of neuro PMU and then RTU.

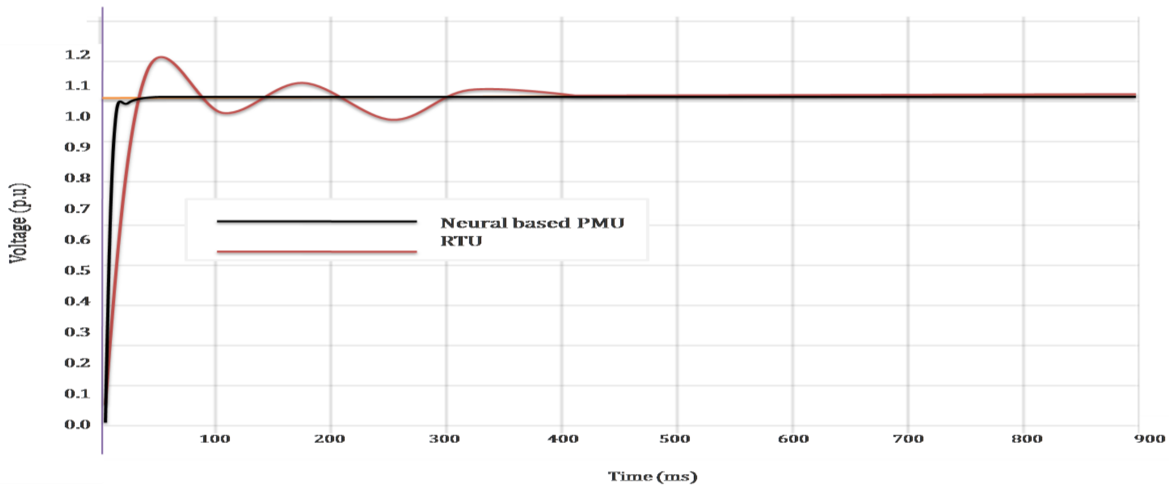

Figure 10: Comparative data monitoring performance

From the comparative result presented in the figure 10, the graph showed the step response performance of the neural network based PMU and RTU. The result when used to sample the voltage magnitude at the bus shows that the settling time which is the total time taken for the

RTU to sample, process and send data to the control centre is 540ms and that of the PMU are 14ms. The implication of the result showed that the ability of the PMU to sample data in real time and the intelligence of the neural network ensures fast data sampling and processing result.

7. CONCLUSION

This study has successfully developed an improved monitoring system for the Alaoji 330/132KV transmission station. The study was achieved using artificial neural network model trained with data collected from Alaoji 330KV substation and then used to improve the conventional PMU to achieve the proposed intelligent PMU system. The new system was deployed at the Alaoji SCADA for examination and the result presented a regression value of 0.984; MSE result of 0.053288Mu, accuracy of 98.3 and response time of 14.3ms is are all very good.

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APPENDIX A (COMPARATIVE DATA ANALYSIS)

Table 3: Comparative Data of the Umuahia 132/33KV bus

Time (hr)	Umuahia 1 with LFSA	Umuahia 2 with LFSA	Umuahia 1 with RTU	Umuahia 2 with RTU
1	0.987332	0.987032	0.981332	0.981032
2	0.958026	0.958026	0.958026	0.958026
3	0.998455	1.000000	0.998455	1.000000
4	0.984424	0.982444	0.984424	0.982444
5	0.746304	0.949304	0.747704	0.947704
6	0.995670	0.995670	0.995670	0.995670
7	0.983432	0.986324	0.983432	0.981724
8	0.843033	0.987268	0.843033	0.981268
9	0.949304	0.978903	0.947704	0.978903
10	0.995670	0.988672	0.995670	0.988672
11	0.965824	0.987060	0.945824	0.981060
12	0.983033	0.986013	0.983033	0.986013
13	0.949304	0.949304	0.947704	0.947704
14	0.995670	0.986324	0.995670	0.981724
15	1.000000	0.987268	1.000000	0.981268
16	0.983033	0.978903	0.983033	0.978903
17	0.681268	0.681268	0.681268	0.681268
18	0.988903	0.988903	0.988903	0.988903
19	0.980632	0.980632	0.980772	0.980772
20	0.891060	0.891060	0.891060	0.891060
21	1.000000	1.000000	1.000000	1.000000
22	0.699970	0.699970	0.699970	0.699970
23	0.988903	0.988903	0.988903	0.988903
24	0.987332	0.987032	0.981332	0.981032

Table 4: Comparative Data of the Aba 132/33KV bus

Time (hr)	Aba 1 with RTU	Aba 2 with RTU	Aba 1 with LFSA	Aba 2with LFSA
1	0.961032	0.981032	0.961032	0.987032
2	0.978026	0.958026	0.978026	0.958026
3	0.988455	0.947704	0.988455	0.949304
4	1.000000	0.995670	1.000000	0.995670
5	0.947704	1.000000	0.949304	1.000000
6	0.995670	0.983033	0.995670	0.983033
7	1.000000	1.000000	1.000000	1.000000
8	0.983033	0.991724	0.983033	0.991724
9	1.000000	0.997640	1.000000	0.997640
10	0.981724	0.986013	0.986324	0.986013
11	0.977640	0.947704	0.963640	0.949304

12	0.985413	0.995670	0.985413	0.995670
13	0.985623	1.000000	0.985623	1.000000
14	0.947704	0.983033	0.949304	0.983033
15	0.995670	1.000000	0.995670	1.000000
16	1.000000	0.981724	1.000000	0.986324
17	0.983033	0.981268	0.983033	0.987268
18	0.988903	0.978903	0.988903	0.978903
19	0.980772	0.988672	0.980632	0.988672
20	0.891060	0.981060	0.891060	0.987060
21	1.000000	1.000000	1.000000	1.000000
22	0.699970	0.699970	0.699970	0.699970
23	0.988903	0.988903	0.988903	0.988903
24	0.961032	0.981032	0.961032	0.987032

Table 5: Comparative Data of the Owerri132/33KV bus

Time (hr)	**Owerri 1 with RTU**	**Owerri 2 with RTU**	**Owerri 1 with LFSA**	**Owerri 2 with LFSA**
1	0.981032	0.947704	0.987032	0.949304
2	0.958026	1.000000	0.958026	1.000000
3	0.998455	0.983033	0.998455	0.983033
4	1.000000	0.981724	1.000000	0.986324
5	0.947704	0.981724	0.949304	0.986324
6	0.995670	0.995670	0.995670	0.995670
7	1.000000	0.987775	1.000000	0.986375
8	0.983033	0.843033	0.983033	0.843033
9	0.947704	0.947704	0.949304	0.949304
10	0.995670	0.995670	0.995670	0.995670
11	1.000000	0.981724	1.000000	0.986324
12	0.983033	0.983033	0.983033	0.983033
13	0.981724	1.000000	0.986324	1.000000
14	0.981268	0.981724	0.987268	0.986324
15	0.978903	0.977640	0.978903	0.963640
16	0.988672	0.985413	0.988672	0.985413
17	0.681268	0.681268	0.681268	0.681268
18	0.988903	0.981724	0.988903	0.986324
19	0.980772	0.981268	0.980632	0.987268
20	0.891060	0.978903	0.891060	0.978903
21	1.000000	0.988672	1.000000	0.988672
22	0.699970	0.699970	0.699970	0.699970
23	0.988903	0.988903	0.988903	0.988903
24	0.981032	0.947704	0.987032	0.949304

Table 6: Comparative Data of the Afam 132/33KV bus

Time (hr)	**Afam1 with LFSA**	**Afam 2 with LFSA**	**Afam1 with RTU**	**Afam 2 with RTU**

1	0.987032	0.949304	0.981032	0.947704
2	0.968026	0.986324	0.968026	0.981724
3	0.988455	0.987268	0.988455	0.981268
4	1.000000	0.978903	1.000000	0.978903
5	0.786304	0.988672	0.787704	0.988672
6	0.975670	0.987060	0.975670	0.981060
7	1.000000	0.986324	1.000000	0.981724
8	0.893033	0.681268	0.893033	0.681268
9	1.000000	0.988903	1.000000	0.988903
10	0.986324	0.986324	0.981724	0.981724
11	0.987640	0.987268	0.987640	0.981268
12	0.976013	0.978903	0.976013	0.978903
13	0.949123	0.988672	0.966123	0.988672
14	1.000000	0.987060	1.000000	0.981060
15	1.000000	0.986324	1.000000	0.981724
16	1.000000	0.987268	1.000000	0.981268
17	0.791268	0.681268	0.791268	0.681268
18	0.978903	0.988903	0.978903	0.988903
19	0.989632	0.980632	0.989772	0.980772
20	0.895060	0.891060	0.895060	0.891060
21	1.000000	1.000000	1.000000	1.000000
22	0.889970	0.699970	0.889970	0.699970
23	0.958903	0.988903	0.958903	0.988903
24	0.987032	0.949304	0.981032	0.947704