Enhancing Realtime Supervision and Control of Industrial Processes over Wireless Network Architecture Using Model Predictive Controller

Ulagwu-Echefu A.[1], Eneh .I.I.[2], Chidiebere U.[3]

[1,2]*Enugu State University of Science and Technology, Nigeria*

[3]*Destinet Smart Technologies, Nigeria*

***Abstract*: This paper presents enhancing real-time supervision and control of industrial processes over wireless network architecture using model predictive controller. The research reviewed various related literatures on Real Time Operating Center (RTOC) and their importance on industrial control systems. From the review it was observed that one of the major components of RTOC is the Remote telemetry Unit (RTU) or Programmable Logic Controller (PLC). These systems are embedded with Proportional Integral Differential (PID) controllers for processing of data collected and transmitted to the RTOC monitor via the communication bus; however the delay response time of the PID controllers induce latency on the data transmitted, thus affecting the quality of RTOC analysis and as a result has remained a major problem all over the world. This problem was addressed in this research using artificial neural network (ANN) based model predictive controller. The ANN was trained using data collected from an oil and gas drilling process to develop a predictive model which was used to collect time series data of the plant and send to the RTOC monitor in real-time. The system was implemented with Simulink and the performance was evaluated. The result showed that the predictive controller was able to collect data and transmit to the RTOC at 22.5ms, which according to IEC 60870-6 and IEC 62591 Standard for RTOC satisfy the requirement for real-time and better then the 40ms achieved in the conventional system.**

***Keywords*: Real-Time, RTOC, RTU, PLC, PID, MPC,**

I. INTRODUCTION

Drilling is one of the main processes for the extraction of oil and gas. This step involves the dug of wells or rigs on the earth crust from which crude oil are extracted. During this process various activities with the potential to cause harm occurs such as flammable gas release among other events which are classified according to the occupational Safety and Health Administration (OSHA) as harmful, and has to be monitored and controlled.

In simple terms, monitoring is an observation process where the behavior of a system is analyzed via data collection. In the early 70s, monitoring of offshore oil and gas events like drilling process relied mainly on instrumentation data for analysis and decision making. However, this approach was later improved on due to the advancement in information technology and telecommunication, thus leading to the introduction of information and knowledge based center concept which triggered pilot programs like the Real Time operation Centers (RTOC) [1]. In order words, the concept of real time monitoring is nothing new during the process of drilling among other offshore activities.

According to [2], real time monitoring is the continuous delivery of updated information at approximates zero latency. However, to achieve this has become a major challenge due to the limitations of the information technology system deployed at the drilling site for remote data collection. In many RTOC location, Remote telemetry Unit (RTU) are majorly employed over Programmable Logic Controller (PLC) due to their ruggedness and ability to withstand harsh environment and ability to collect data, process and transmit remotely to the control center for analysis [3, 4, 5]. These RTU are embedded with Proportional Integral Differential (PID) Controllers, sensors and communication bus which works hand in hand for data collection, processing and transmission, however the main challenges with these embedded RTU systems are the issues of poor sensitivity of the sensor and delay response time on the controller which exceeds the requirements in [6, 7, 8, 9, 10] for real time data collection. Hence it is important that an improved system which has the capacity for high data sensitivity and also an enhanced control system be used to optimize the performance of the RTU system to achieve real time data supervision objectives.

To realize this, the study proposed to use Phasor Measurement Unit (PMU) and Model Predictive Controller (MPC). The PMU is a device which uses synchophasor to synchronize and collect data in global positioning satellite time [11], while the MPC uses online process model to approximate time series challenges associated with nonlinear systems. These two devices will be interconnected and used to improve the conventional RTU system for real time supervision process. According to [12], MPC are of many types but the use of artificial neural network MPC provides faster processing time when compared to the rest. This is because the neural network neural network has the ability to learn and make accurate decisions and hence will be trained with data collected from the case study drilling process for reference model, and then uses the intelligence (reference model) for time series predictions. This when achieved will provide reliability, data integrity and help achieve optimal safety of lives and properties during the process of offshore drilling.

II. LITERAURE REVIEW

[13] Developed a large scale and temporal fading channel model for indoor industrial facilities monitoring based on radio frequency. The model was implemented and deployed for the supervision of an industrial facility. The result despite the success can be improved using predictive control. [14] Presented a paper which investigated the effect of latency on industrial wireless network. From the study it was observed that distance between the control center and the field and also the nature of the environment (like offshore shore for oil exploration) can also affect the quality of data integrity via latency. In [15] the effect of packet losses in industrial control technical process system was evaluated. From the research, it was observed that the inability for wireless network to provide reliable networking performance has hindered its adoption in many industrial settings. [16] Used embedded approach which integrated ARM7 processor with Ethernet to achieve near real time supervision performance, but the limitation is the ARM 7 controller are not compatible with basic desktop operating system (like windows) and also the routing performance for time data delivery suffer latency. Having reviewed some of these studies, it is clear that despite the success achieved; there is need for an intelligent system which collects data in real time and transmit to the RTOC for accurate analysis.

III. MATERIAL AND METHODS

The major materials used are PMU based sensing element [11], artificial neural network model predictive controller [12], communication bus, Antenna, transmitter, receiver, human machine interface [12, 16]. These materials were used to develop the improved RTOC based on the specification and guideline according to IEC 60870-6 [19] and IEC 62591 methodology for real time and wireless communication. The artificial neural network was designed and trained to develop a prediction model using data collected from the Nigerian oil and gas industry (Nigerian National Petroleum Corporation (NNPC)) and then deployed for monitoring time series events at the offshore, the data captured for the training were collected by the PMU which uses synchophasor systems to synchronize data in real time, then transmit to the control center via the communication bus. The improved system block diagram is presented in figure 1;

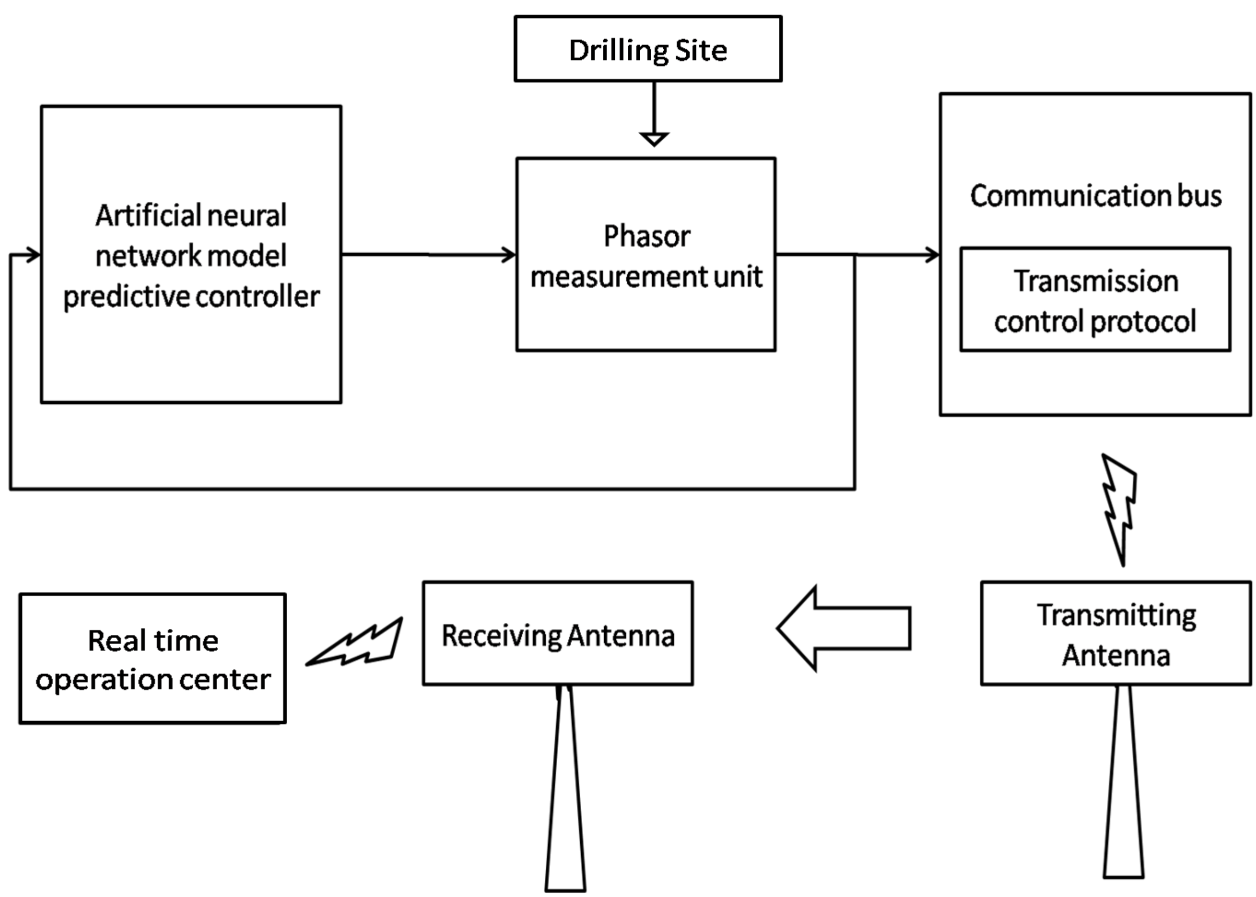

Figure 1: The Improved RTOC

The figure 1 showed how the PMU was used to collect data from the drilling site and process with the neural network predictive controller for real time transmission to the RTOC via the transceiver antenna system.

IV. SYSTEM DESIGN

To design the improved RTOC system, the dynamic model of the drilling process developed in [20] was used as the plant model. Data of the plant was collected using PMU designed in [11] and then feed to the neural network architecture developed in figure 2 for offline training to achieve a reference model of the predictive controller. This reference model was used for time series supervision of the plant dynamics for real time data collection.

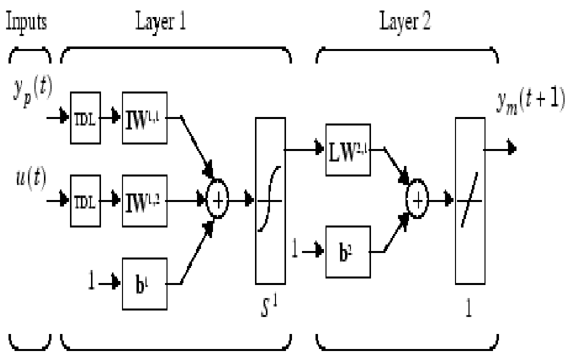

Figure 2: modeling diagram of the ANN

Where $y_p(t)$ is the input time series plant data, u(t) is the input from the training data, S^1 is the summation function, l is the activation function , $y_m(t+1)$ is the time series data to be trained using training algorithm as presented in figure 3;

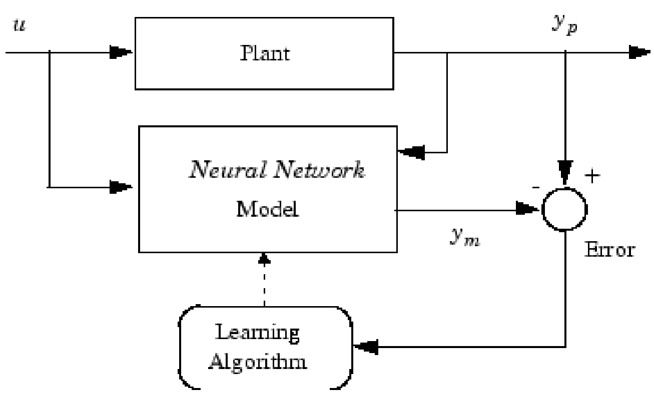

Figure 3: system identification modeling diagram

From the figure 3, the time series data collected were trained by the neural network using back propagation algorithm and generate a predictive model for time series data collection of the dynamic plant behavior. The training algorithm is presented in figure 4;

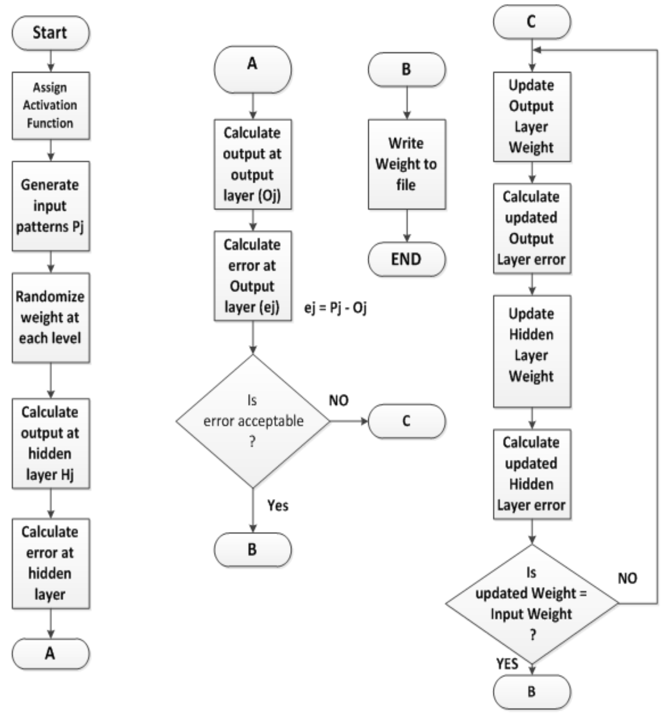

Figure 4: The Back propagation learning algorithm

The back propagation algorithm was used to train the neural network to generate the model predictive control system as shown in equation 1;

$$J = \sum_{j=N_i}^{N_2} (y_r(t+j) - y_m(t+j)^2 + p\sum_{j=1}^{N_u} u^i(t+j-1) - ui(t+j-2))2 \quad \text{Equation 1}$$

The model presented the controller which collects time series data of the dynamic plant behavior. Where N_1, N_2, and N_u define the horizons over which the tracking error and the control increments are evaluated. The u' is the tentative control signal; y_r is desired response, and y_m is the network model response. The ρ value determines the contribution that the sum of the squares of the control increments has on the performance index.

V. IMPLEMENTATION

To implement the new RTOC system developed, the mathematical and modeling diagrams developed were used and deployed with optimization toolbox, neural network toolbox, and Simulink. The plant data collected from [20] was imported into the neural network model in figure 2 and then trains using the training algorithm in figure 4 to generate the predictive control model in equation 1. The implementation tool for the design deployment of the controller and the training is presented as shown in figure 5;

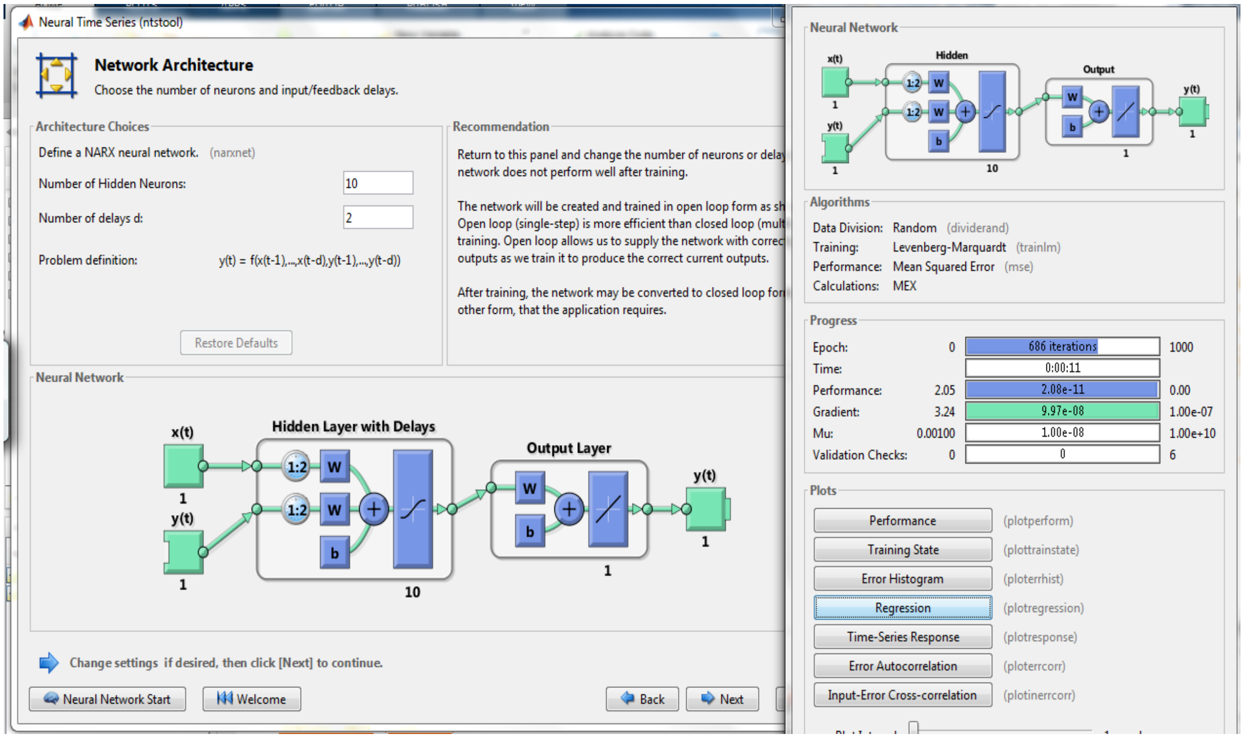

Figure 5: The Simulink of the improved RTOC system

The figure 5 presented the simulink architecture of the neural network based model predictive controller, alongside the training tool for the system. Before training, the neural network tool automatically divide the data collected into three multi set of test, train and validation set in a ratio of 70:15:15; then training was done using the parameters in table 1.

Table 1: Simulation parameters

Parameters	Values
Size of hidden layers	10
Training epochs	1000
Controller training segments	100
No. delayed reference input	2
Maximum feature output	3.1
Number of non hidden layers	2
Maximum interval per sec	2
No. delayed output	1
No. delayed feature output	2
Minimum reference value	-0.7
Maximum reference value	0.7

Performance Evaluation

To evaluate the performance of the improved RTOC system developed, the Mean Square Error (MSE) analyzer model in [21] was employed as;

$$MSE = \frac{1}{N}\sum_{n=1}^{N}[S_o(n) - S_f(n)]^2 \quad \text{Equation 2}$$

Where S_o is the reference predictive control model in equation 1; S_f is the time series data collected and n is the number of data sample collected, N is the average time for n sample of data collected. The other model used for the evaluation of the controller is the step response time model adopted from [21] and was used to compute the response of the RTOC performance.

VI. RESULTS AND DISCUSSIONS

Recall that in section (iv) the plant data was automatically divided into three multi sets for training, test and validation. The result presented their performances using the MSE model in equation 2. The aim here is to achieve a MSE value equal or approximately MSE=1; the result is presented in figure 6;

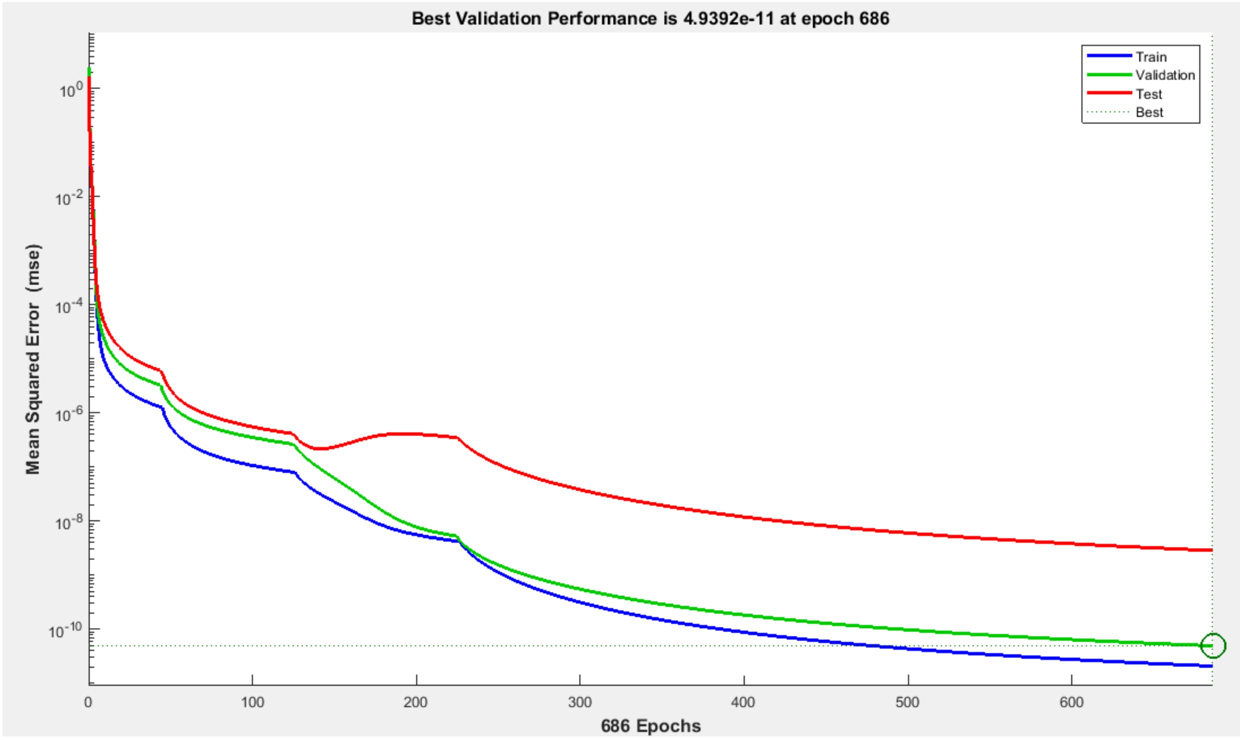

Figure 6: MSE performance of the predictive controller

The result shows that the MSE value achieved is 0.00100 after 686 iterations of epoch values. From these result, the implication shows that the predictive controller perfectly learn the data and make accurate time series data collected. For better investigation the regression graph in figure 7 was used which discussed the regression value for each multi sets.

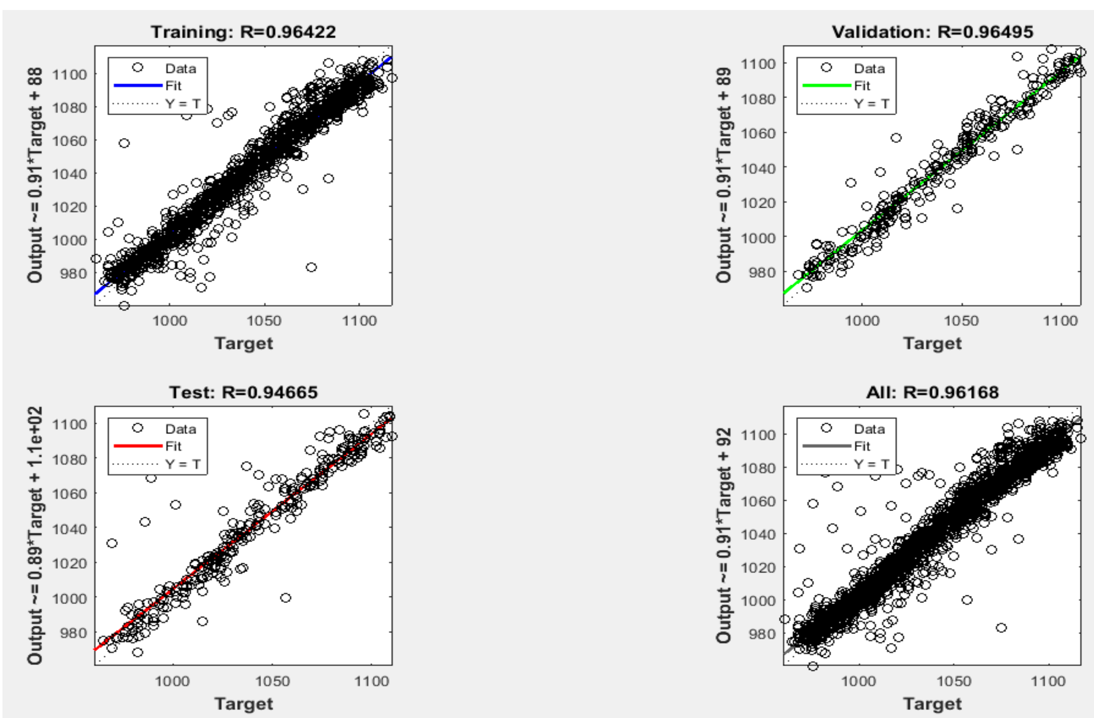

Figure 7: The Regression performance

From the regression result, it was observed that the training process achieved an accurate regression performance with an R=0.96422; when the predictive controller was used tested on the oil and gas plant for data collection, the regression value is R=0.94665. The aim here is to achieve a regression equal or approximately R=1; from the result achieved it was observed that the average R value achieved in the study for the multi sets is 0.96168 which is the overall regression value. The next result presented the step response performance of the system when deployed as an improved RTOC system for supervision and time series data acquisition in the oil and gas plant under study as shown in the RTOC monitor in figure 8;

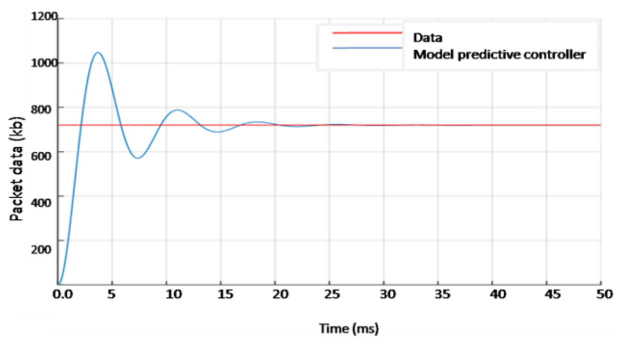

Figure 8: The Step response of the new RTOC system

The result in figure 8 shows the time take for the new predictive control system to collect data and send to the monitoring section based on the step response model in [21]. The result shows that the controller detect the PMU data at 2.2ms, process and transmit to the RTOC monitor at 22.5ms. The result showed that the new RTOC system was able to perform monitoring in real time going by the standards and specification of IEC 60870-6 requirements and also the recent work of [9] which achieved 40ms.

VII. CONTRIBUTION TO KNOWLEDGE

Having completed this research, the following were contributed to knowledge;

i. A neural network based model predictive controller was developed and used to improve RTOC system performance for drilling process supervision
ii. The research achieved a data collection time of 22.5ms against 40ms achieved in [9].

VIII. CONCLUSION

PLC/RTU is the most vital components used in the present day RTOC system; however the delay response time in the PID controller embedded with these (RTU/PLC), induces latency which affects the integrity and reliability of data collected and analysis. This has become a major challenge and has hindered the effective application of RTOC in many industrial settings today. This problem was rectified improving the PLC/RTU using artificial neural network based model predictive controller. The controller was developed and used to replace the PID logic solver in the conventional RTOC setup. The result showed that the new system satisfied the RTOC requirement according to IEC 60870-6 methodologies and will provide reliable data for analysis and hence improve quality assessment and overall RTOC performance in the oil and gas industry among others.

REFERENCES

[1] Bureau of Safety and Environmental Enforcement (BSEE) (2014) “An assessment of the various types of real time data monitoring system available for offshore oil and gas operations” E12PC00063
[2] Tech Target Contributor (2020) “Real time monitoring” Article
[3] Tom Wilson, PLC Based Substation Automation and SCADA (1999), Systems and Selecting a Control System Integrator, Presented at the Western Electric Power Institute Distribution/Substation Automation Workshop.
[4] Qura tul Mudassir S. (2015) “Implementation of SCADA for multiple telemetry units while using GSM for communication”, Journal of IEEE.
[5] Kezunović M. Latisko N. Ved (2012) “Real-Time Monitoring and Assessment of Circuit Breaker Operations for Diagnostics and Control Applications,” EPRI Substation Equipment Diagnostics Conference XIII, New Orleans, Louisiana, March, 2016.
[6] ITU – T_G.1010 (International telecommunication union telecommunication) end user multimedia services categories. Quality of service and performance, 2009.
[7] ITU-T-G114 (2014) “Recommendation G.114”, One way transmission time.
[8] Bowen C., Buennemeyer, and R. W. Thomas, “Next Generation SCADA Security : Best Practices and Client Puzzles,” in Proceedings of the 2005 IEEE Workshop on Information Assurance and Security United States Military Academy, West Point, NY, 2005.
[9] Suznjevic M., Saldana J. (2015) “ Dleay limits for real time services draft” TAWGID;
[10] Martinez C., Parashar M, J. Dyer, and J. Coroas (2015) “Phasor Data Requirements for Real Time Wide-Area Monitoring, Control and Protection Application‘‘; IEEE Vol. 4; Issue 5; Pp 453 – 459.
[11] Ulagwu E., Anthony C (2021)”Development of Robust monitoring and control system for closed loop industrial process control over wireless” PhD thesis; (Unpublished);
[12] Http: //www. Mathworks.com/help/artificial neural network
[13] Tanghe E, et al. The Industrial Indoor Channel: Large-Scale and Temporal Fading at 900, 2400, and 5200 MHz. IEEE Trans Wireless Comm. 2008 Jul;7(7):2740–2751.
[14] Saifullah A, et al. End-to-End Communication Delay Analysis in Industrial Wireless Networks. IEEE Trans Comput. 2015 May;64(5):1361–1374.
[15] Yongkang Liu, Richard Candell, and Nader Moayeri (2017)”Effects of Wireless Packet Loss in Industrial Process Control Systems” NIST Public Access; vol 68; pp412-424.
[16] Potdar Snehal Dilip1 & S. R. Jagtap (2013) “Remote Monitoring & Controlling Of Real Time Industrial Parameters With Gsm & Ethernet” International Journal of Electronics, Communication & Instrumentation Engineering Research and Development (IJECIERD); ISSN 2249-684; Vol. 3, Issue 3, Aug 2013, 1-10
[17] McCarthy J. (2007) “What Is Artificial Intelligence?” Technical report, Stanford University (Accessed August 18, 2021).
[18] Mehta A (2019) “ Machine learning”: https://www.digitalvidya.com/blog/types-of-neural-networks/ (Ac Accessed August 18, 2021).
[19] IEC 62591 Ed. 1.0 b: 2010, “Industrial Communication Networks—Wireless Communication Network and Communication Profiles—Wireless HART™,” 2010.
[20] Peilun O., Wehua C. Min W., Chao G (2019) “ Design of Intelligent drilling system software framework and data architecture based on MVC pattern” CCC.
[21] Emenike Ani (2021)” Real time flood monitoring and detection system” Master’s thesis; UNIZIK (Unpublished).