MODELLING OF A RECURSIVE POLYNOMIAL ESTIMATOR WITH MACHINE LEARNING TO IMPROVE SAFETY INTEGRITY LEVEL OF PETROCHEMICAL PROCESS DESIGN

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Initial submission 4/5/2024; Final submission 28/6/2024; Publication 7/7/2024

ABSTRACT

This paper presents the application of machine learning technique and recursive polynomial estimator for improving the reliability of critical safety instrument system. The aim of the research is to improve the reliability of critical safety instrument system using machine learning technique and the main objective to develop a neuro logic solver and polynomial estimation model which monitoring the behaviour and distillation plant and control against system failure. To address this problem, literatures were reviewed, and a gap on the safety integrity was identified. This was done using methods such as risk assessment test, data collection, neurologic solver algorithm and error estimation algorithm and guided by the International Electrochemical Commission (IEC) 61508 and 61511 methodologies for the design and implementation of Safety Instrument System (SIS). The neurologic solver algorithm was developed using artificial neural network, tansig activation function and gradient descent back-propagation algorithm, while the error estimation algorithm was developed with recursive polynomial functions. These algorithms were implemented with Simulink, evaluated and cross validated considering Mean Square Error (MSE), regression, PFD, Risk Reduction Factor (RRF) and Safety Integrity Level (SIL). The result of the neurologic solver MSE is 2.98E-09, Regression is 0.9978 and PFD is 9.00E-04. When the neurologic solver was integrated on the testbed and evaluated, the PFD is 8.52E-04, thus presenting a SIL of 4 as against 1.14E-03 in the test bed with neurologic PLC solver and hence SIL of 3. The overall neurologic-based SIS PFD is 6.44E-03 and RRF of 155.279 as against 6.72E-02 with RRF of 14.881 which is characterized with PLC based logic solver, recording a 33.8% improvement in reliability.

Keywords: Safety Instrument System; Recursive Polynomial Estimator; International Electrochemical Commission; Safety Integrity Level; Risk Reduction Factor; Probability of Failure on Demand; Machine Learning

1. INTRODUCTION

Accident in process plant is a regular occurrence, especially in high-risk process industries. These events keep occurring despite the strict adherence of the industries to the basic theories and standards of alarm management and process safety. The standard provides the various types of protection schemes necessary to reduce the level of risk to the lowest tolerable state. These standards build layers of protection which monitor and guard against nonlinear process incident during the manufacturing process. However, majority of hazards occur due to the failure of many of these organizations in the implementation of the best protection scheme, compatible with the level of risk their technical process offers. These as a result lead to various effects such as explosion, tanks overflow, chemical or gas leakages, loss of workers lives, industrial facilities, costing a lot among other socio economic and geographical impacts it has on the world. To rectify these challenges, appropriate safety implementation needs to be adopted in these industries according to the safety standard of the Occupational Safety and Health Administration (OSHA)and International Electrochemical Commission (IEC) regulations (Rafal, 2016).

One of the major sectors which practice the use of power plant is the oil and gas industry. This industry is responsible for the extraction of natural crude from mother earth and then fractionally distils the raw material at a very high temperature and pressure, to produce multiple products such as petrol, natural gas, kerosene, cooking gas, bitumen among other numerous bye products. The importance of crude oil in the global industrial and economic sector today cannot be overemphasized, which include the vital output it produces and the economic and foreign benefits it attracts. However, the technical process of producing these products involves dangerous risks due to the high pressure, concentration, temperature, among other variables involved in the fractional distillation process within a plant.

In order to minimize these risks, process control systems are installed to maintain a safe operation of the plants. These systems are operated by trained control system engineers and assisted by robust alarms to intelligently detect fault and alert the operators for safety measures. Safety Instrument System (SIS) is an additional layer of protection scheme above the process design, process control and alarm layer in process industrial safety. According to David (2016), it's a system which consists of basic technologies that are separate from the basic process control systems, to isolate them from the problem that they are intended to identify and prevent. The three basic elements of SIS are the sensors, logic solvers and the final control elements. An SIS is designed to mitigate industrial hazardous events such as explosion, fire, etc. by taking a process to a safe state when pre-determined conditions are violated. Other common terms used are safety interlock systems, Emergency Shutdown Systems (ESD), and Safety Shutdown Systems (SSS). Each SIS has one or more Safety Instrumented Functions (SIF). Every SIF within an SIS will have an SI level. These Safety Integrity Level (SIL) may be the same, or may differ, depending on the process (Dele, 2017).

SIL is a measure of safety system performance, in terms of Probability of Failure on Demand (PFD). This convention was chosen based on the fact that it is easier to express the probability of failure rather than that of proper performance (e.g., 1 in 100,000 vs. 99,999 in 100,000). There are four discrete integrity levels associated with SIL; these are the SIL 1, SIL 2, SIL 3, and SIL 4. The higher the SIL, the higher the associated safety level, and the lower probability that a system will fail to perform properly. As the SIL increases, typically the installation and maintenance costs and complexity of the system also increases. Specifically for the process industries, SIL 4 systems are so complex and costly that they are not economically beneficial to implement. Additionally, if a process includes so much risk that SIL 4 system is required to bring it to a safe state, then there is a fundamental problem in the process design that needs to be addressed by a process change or other non-instrumented method (Rafal, 2016).

The most used programmable logic solver in the manufacturing industries today is the Programmable Logic Controller (PLC). This is a digital device used for the automation of electromechanical processes which includes fractional distillation, mining, control of machinery on factories assembly lines among others. Unlike the traditional general-purpose computers, the PLC is designed to enable multiple input ports and output ports arrangements, resistance to noise, immunity to vibration, extended temperature ranges and also the capacity to control multiple devices over in a timely manner. This PLC is controlled based on programs and are battery powered and backed up with a non-volatile memory (Anup, 2015).

The functionalities of the PLC have evolved overtime to add sequential distributed control system, relay control, process control and networking. The data handling, processing capacity, power, communication and storage capabilities of the modern-day PLC are of the same speed with the present minicomputer class. PLC today have been made more intelligent to adapt to varying industrial processes (Inyama and Agbaraji, 2015).Industries and organizations especially their health and safety departments would love to know in advance when the next injury or incident is going to happen to their personnel. Well, technology hasn't gone that far yet, but it has certainly come to a point where it is able to predict this information with a certain accuracy rate. Specially trained Artificial Intelligence (AI) data models can look and deeply analyze a whole lot of historic data from various aspects and can predict the injury or incident rate with certain level of accuracy (Calvet and Arkun, 2018; Phillips and Habour, 1996). Safety measures taken by companies like creating awareness, providing training and calling regular safety meetings for their personnel makes a direct impact on the company's incident rates. Therefore, by looking at these and other activities the Machine Learning/Artificial Intelligence (AI) models can learn and predict the possible incident rate at any given time. Frequent safety audits, audit recommendations and action items can only add to refine the quality of these incident rate predictions. Some Safety Management Systems have already started plugging in this module within their system and offering their clients to take full advantage of this machine learning process (Dash et al., 2001).

Various studies such as (Rafal, 2016; Jasjeet and Matthew, 2016; Edgar and John, 2014; Dele, 2017; Abhinav and Rajiv, 2018; Tan et al, 2015; Al-Muthairi and Zbiri, 2018; Ricardezet al. 2018; Hori and Skogestad, 2018) presented different approaches for ensuring safety instrument system and improving on the safety integrity level of technical processes on an industrial scenario, meanwhile, the Probability of Failure on Demand (PFD)of this logic component remains a threat to the safety integrity of the SIS and has remained a gap to be addressed. To solve this problem, a machine learning based logic solver will be developed to improve control response and performance, while the integrity will be improved using mathematical estimation model to detect step ahead error of the plant and activate safety measures.

2. METHODOLOGY

The methodology adopted for the development of the new SIS was guided by the IEC 61508 and IEC61511 standards which required that the safety and reliability standard of each individual component in the SIS is attained. The study begins with the risk analysis of the technical process with major focus on the probability of failure on demand of the SIS components to decide the safety integrity level. From the assessment, the critical safety component with potential for dangerous failure was identified and then a machine learning algorithm was used to develop a more reliable solution and implemented on the testbed with simulation. The safety integrity level was analyzed and compared with the characterized testbed for percentage improvement.

2.1 Data Acquisition

Having successfully performed the risk assessment test on the SIS, the data was collected considering the PFD of the system components, the detected and undetected common cause failures, diagnostic coverage for each component for a period of 39 days. The data are reported in the next chapter and analyzed considering the usage of safety integrity level and risk reduction factor according to the IEC standard. Another data of the fractional distillation plant was also collected from the case study containing attributes such as the temperature and pressure behaviour of the plants and was used later in the work for development of the machine learning based algorithm proposed.

2.2 LOGIC SOLVER SYSTEM BASED ON MACHINE LEARNING

In this section, machine learning based logic solver is developed using artificial neural network, activation function and training algorithm to reduce most of these technical problems attributed with the conventional PLC based logic solver and hence reduce failure probability to the minimum. The neural network model was developed using the interconnection of neurons, activation functions, training algorithms. The model presents how the neurons which have weights and bias was configured according to the input data class of the training set, the activation function and training algorithm to learn the distillation plant data collected and generate a neural network-based logic solver algorithm. The activation function used is the Tangent sign mode (tansig) activation function which enables the neurons to activate and also ensure data convergence between (-1 and 1). The training algorithm used in the study, is the Gradient descent back propagation type as it allows the neurons to learn, check its learning rate and feedback for adjustment and continuous learning until the least error is achieved.

The data of the plant loaded into the neural network was used to configure the network and then train the neuron with the training algorithm to generate the neurologic solver algorithm. During the training, at each epoch the regression and training error was checked until least error is achieved and then the neuro logic solver algorithm developed as shown in the pseudocode below;

2.3 The Logic Solver Algorithm

1) Start
2) Load plant data
3) Configure neural network with table 1
4) Initialize training algorithm
5) Train neural network
6) Check for training failure
7) If

8) Failure probability ≈ 0
9) Generate logic solver algorithm
10) Else
11) Back-propagation
12) Adjust neuron
13) Repeat step (5; 6; 7 and 8)
14) Generate logic solver algorithm
15) Else
16) Do (step 13) until step 8 is true
17) Generate neurologic solver algorithm
18) Generate the neurologic solver block
19) End if
20) End if
21) End

Table 1: The training parameters

Training Parameter	Assumed Value
Learning Rate	0.001
Number of Epochs	100
Batch Size	32
Activation Function	ReLU
Loss Function	Mean Squared Error (MSE)
Optimizer	Adam
Regularization Techniques	L2 Regularization (weight decay)

The training parameters in Table 1 present the neural network properties which values for input layer and hidden layers were inspired by the plant attributes (class in the training set collected), other values were standard neural network properties auto input by the neural network tool used for training. The flow chart of the SIS developed with the neurologic solver is presented below.

2.4 Safety Integrity Algorithm for the Neuro SIS

The previous section developed a neurologic based SIS system to monitor the distillation plant overflow and maintain stability, however despite the high-level intelligence of the logic solver as it has been trained with the plant data, there is still probability of failure due to common cause problems. To address this, a recursive polynomial estimation model was developed which identifies common cause problems for individual component error ahead of time and control. The model of the recursive polynomial estimation was developed from the general linear dynamic model of the SIS behaviour as an Auto Regressive Moving Average (ARMAX) (Petr, 2014) in equation 1;

$$y(k) = \frac{B(q^{-1})}{A(q^{-1})P\,(q^{-1})}u(k) + \frac{C(q^{-1})}{A(q^{-1})D(q^{-1})}n(k) \qquad 1$$

Where y(k) is the output signal, u(k) is input signal, n(k) is noise with constant variance, A, B, C, D,and P are all shift transfer operators polynomial as shown in the transfer functions below;

$$A(q^{-1}) = 1 + a_1 q^{-1} + \ldots\ldots\ldots.. + a_{na} q^{-na}$$

$B(q^{-1}) = b_1 q^{-1} + b_2 q^{-2} + \ldots\ldots\ldots\ldots + b_{nb} q^{-nb}$
$C(q^{-1}) = 1 + c_1 q^{-1} + \ldots\ldots\ldots\ldots + c_{nc} q^{-nc}$
$D(q^{-1}) = 1 + d_1 q^{-1} + \ldots\ldots\ldots\ldots + d_{nd} q^{-nd}$
$P(q^{-1}) = 1 + p_1 q^{-1} + \ldots\ldots\ldots\ldots + d_{np} q^{-np}$

The ARMAX in equation 1 presented the polynomial regression of the SIS, while the corresponding predictor is presented as(Chan and Zhang, 2011);

$$\breve{y}(t_k|p) = \phi^T (t_k.p)\breve{p}(t_{k-1}) \quad 2$$

Where $\phi^T(t_k)$the repressor, p is the parameter vector and are defined as;

$\phi^T(t_k) = [-y(t_{k-1}) \ldots\ldots \quad - y(t_{k-n_a})\, u(t_k) \ldots\ldots\ldots\ldots\, u(t_{k-n_b}).^T$

$p = [a_1 \ldots\ldots\ldots\ldots a_{na} b_o \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots b_{nb]^T}$

The model in equation 2 was rewritten as a general recursive algorithm in equation 3(Cao and Schwartz, 1999; Chan and Zhang, 2011) which is the estimated step ahead prediction model of the SIS error;

$$\breve{p}(t_k) = \breve{p}(t_{k-1}) + u(t_k)L(t_k)\varepsilon(t_k) \quad 3$$

WhereL(t_k) is the adaptation gain, $u(t_k)$ is the scalar,$\breve{p}(t_k)$ is the estimated time varying vector parameter, $\varepsilon(t_k)$ the predictor error and given as equation 4 with $\breve{y}(t_k|p)$ defined (2)

$$\varepsilon(t_k) = y(t_k) - \breve{p}(t_k|p) \quad 4$$

The Recursive Polynomial Predictor algorithm

1. Start
2. Identify the SIS as ARMAX in equation 1
3. Define the shift transfer polynomials (A, B, C, D, P) and noise function n(k)
4. Get the equivalent SIS predictor model with equation 2
5. Transform to recursive form with equation 3
6. Identify the estimated time varying vector $\breve{p}(t_k)$
7. Identify the predictor error $\varepsilon(t_k)$
8. Return
9. Stop

The algorithm of the polynomial model developed for the optimization of the SIS integrity level operates as follows. First, the SIS model was identified as an autoregressive moving average function using the model in equation 1 with the polynomial equivalent shift operators, noise and input functions. The predictor of the ARMAX in equation 1 is presented as equation 2 which was used to estimate the next behaviour of the SIS and identifying any error in the components using the recursive form in equation 3 with the error estimated defined as equation 3.

Figure 1 present the complete system flowchart which shows the neuro-based SIS and the polynomial estimation model was used to monitor the technical process for tank overflow. When the process control fails, then sensors send the signal to the neurologic solver which then activates the control valve for stability of the reactor. However, when the controller suffers common cause problem the estimation algorithm detects it and then control the plant to prevent failures. Figure 2 present the architectural model of the new SIS and the mathematical estimation model used for the error monitoring. The sensors collect data of the plant and send to the neuro logic solver for control process. The mathematical model was also used to monitor the SIS for common cause problem which can lead to system failure and prevent it. This was achieved identifying the SIS as ARMAX and then transform it into a recursive polynomial estimation model to detect error and also predict the system behaviour as in equation 3.

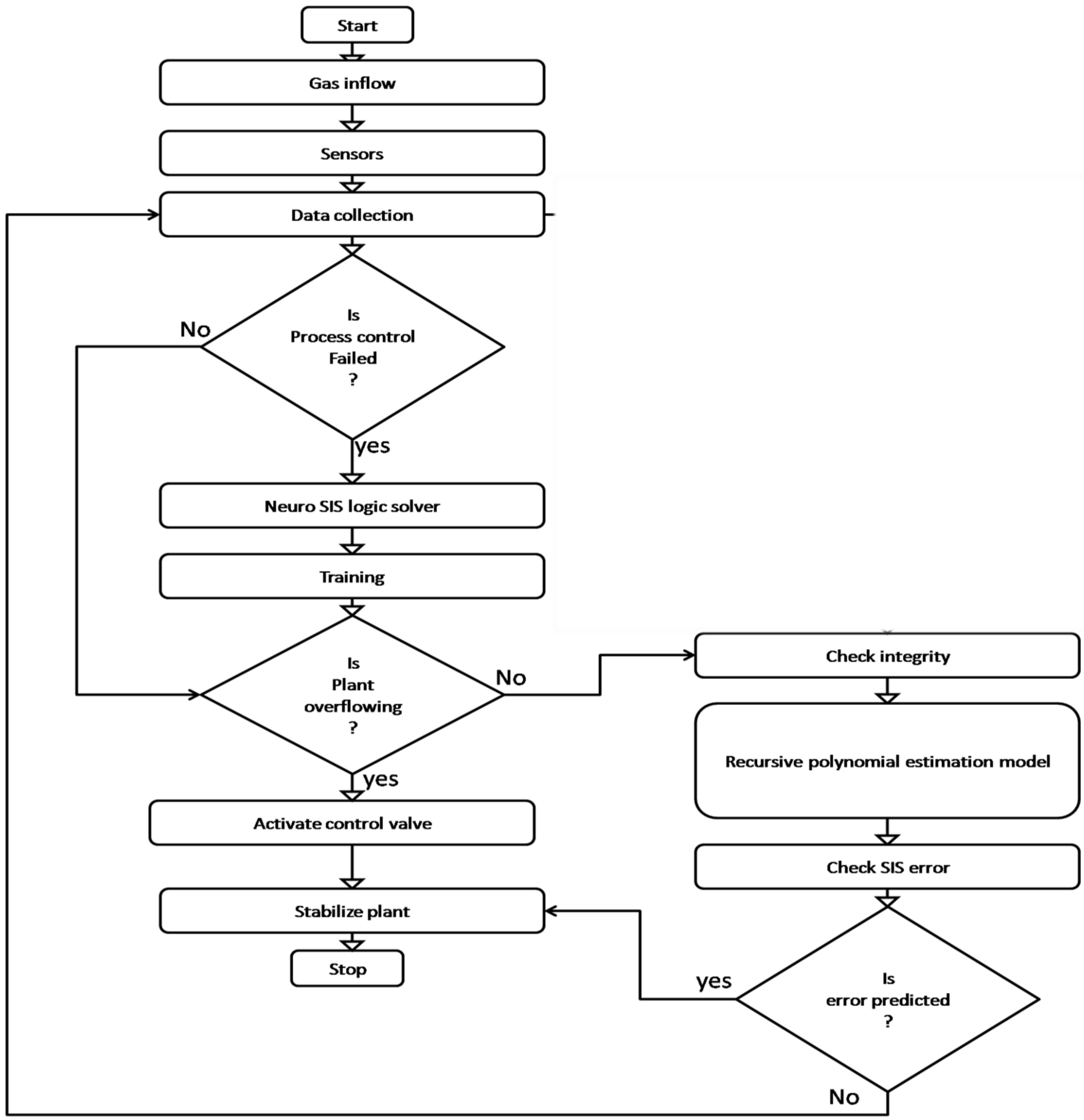

Figure 1: The complete system flowchart

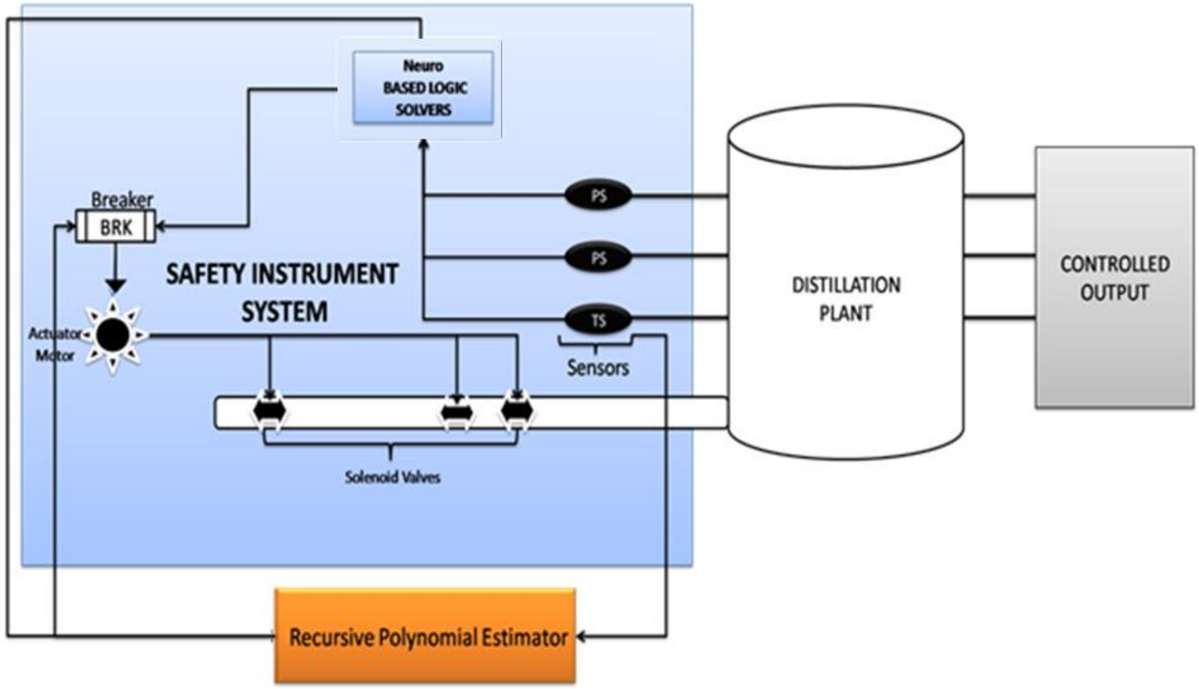

Figure 2: Architectural model of the new SIS

3. SYSTEM IMPLEMENTATION

The neuro-based SIS was developed using the models of the testbed which showed the distillation plant, the sensors, the logic solvers and the final control elements. The study focused on the logic solver with many limitations and probability of failure due to common cause problems. Model of the new SIS was developed using artificial neural network and the mathematical transfer function

During the training process the recursive polynomial estimation function was used to check the system integrity via identification of the SIS as ARMAX in equation 1 and then used the recursive model in equation 3 to identify possible problem for control measures. The transfer function of the recursive polynomial estimation model is presented in figure 3;

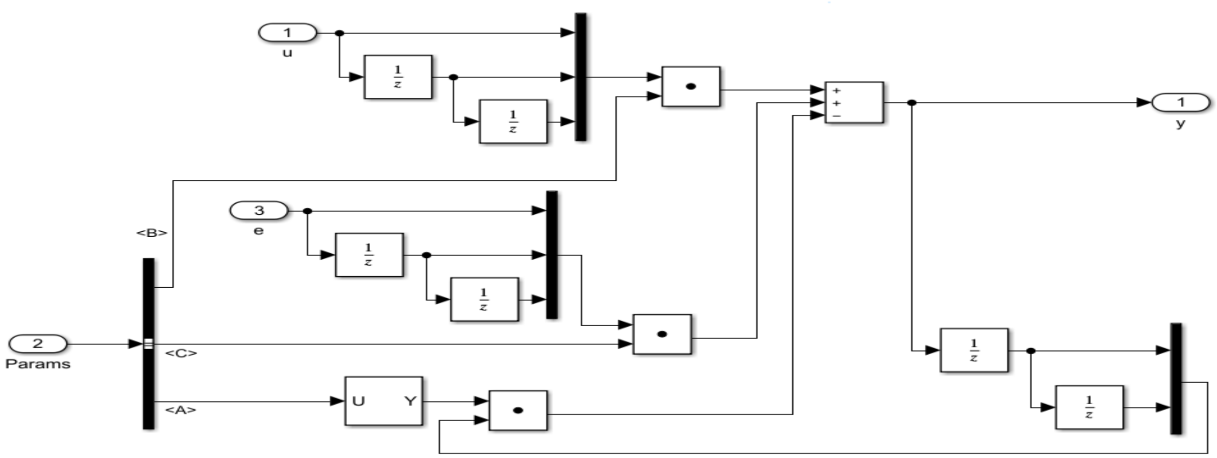

Figure 3: Transfer function model of the recursive polynomial estimator

The figure 3 present the recursive polynomial mathematical transfer function which identify the SIS as an ARMAX, then regression was used to get the predictor and then apply recursive polynomial model in the equation 3 used for the detection of SIS error and estimation.
These models were all implemented using neural network toolbox, system identification toolbox, optimization toolbox and Simulink. The neural network tool was loaded with the plant data and then trained for the generation of the neurologic solver algorithm. The optimization toolbox was used to implement the recursive polynomial algorithm developed, which identified the plant behaviour using the system identification toolbox as ARMAX for monitoring and control measures. The Simulink block of the neuro-based SIS is shown in figure 4;

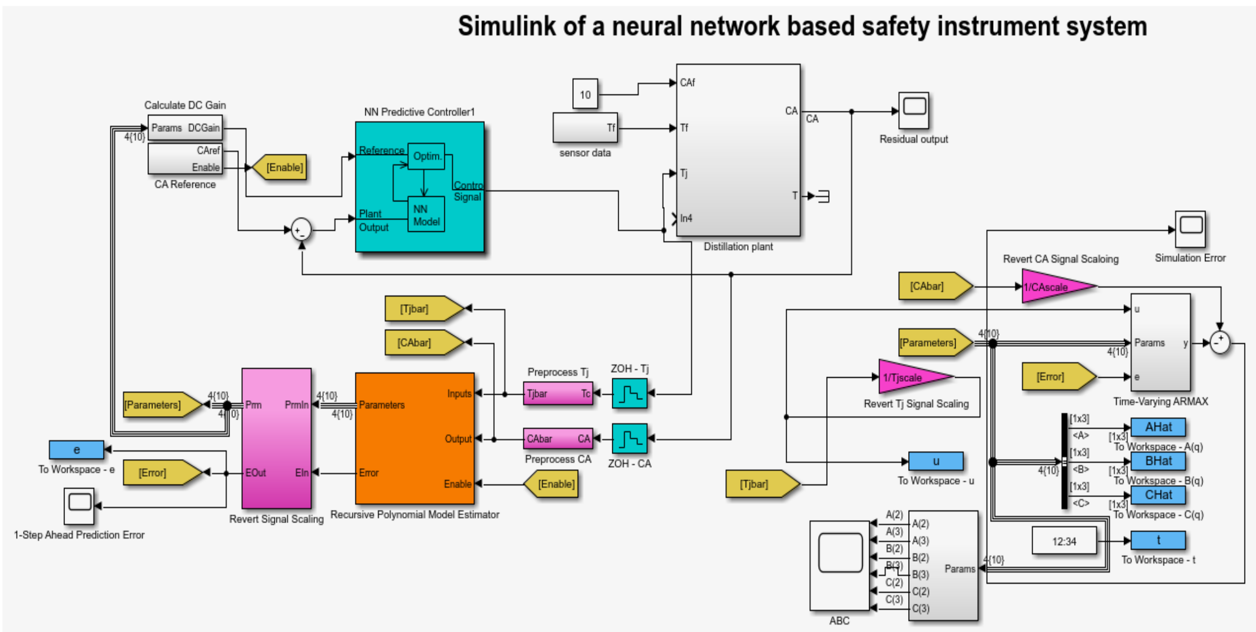

Figure 4: The Simulink model of the Neuro based SIS system

The Simulink implementation of the system was presented in the figure 4, showing how the recursive polynomial estimation model developed was used to improve the safety integrity level of the SIS via monitoring and detection of errors. The neural network was trained as the safety integrity logic solver to monitor the behaviour of the distillation plant, while the polynomial was used to monitor various errors through the time varying Auto Regressive Moving Average (ARMAX) which can occur within process design and the notify through the revert signal scaling scope. While the neural network collects plant data from the process design, the compares with the neural network reference model to control the plant. The simulation of the model was done using the parameters inspired from the test bed as shown in table 2;

Table 2: Simulation parameters

Parameters	**Values**
Simulation time	800Hrs
Time interval	200Hr
Step change	0.5 to 2 (kgmol/m^3)
Noise power	0.0075(k^2)

White noise power	0.015
Signal to noise ratio	10
Deviation of noise level	2%

Table 2 presents the simulation parameters inspired from the case study characterized. The parameters were used to simulate the testbed under the same condition it was characterized, but with the neurologic based SIS developed.

4. RESULTS AND DISCUSSION

From the risk assessment test conducted, it was uncovered that the PLC based logic solver has potential for dangerous failure as it is one of the most vital components of the SIS. This study developed neural network-based logic solver as shown in the figure 3.9 and used to improve the integrity of the SIS.

The performance of the neurologic solver was evaluated using regression and Mean Square Error (MSE) model as appeared in (Inyama and Azubuike, 2015). The MSE performance was presented in figure 5;

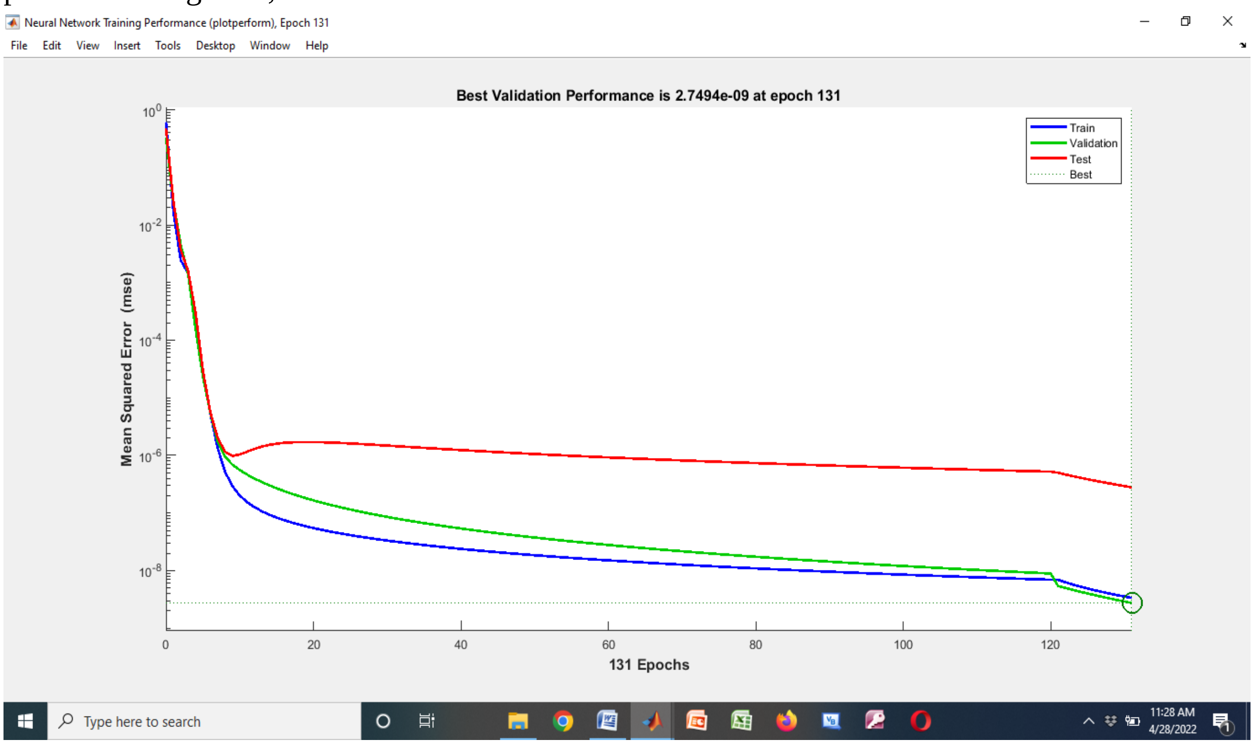

Figure 5: The MSE of the neurologic solver

The analysis of the results depicted in Figure 5 provided valuable insights into the accuracy and effectiveness of the neural network training and testing process. The primary objective of this assessment was to minimize the error associated with the neurologic solver algorithm. Remarkably, the achieved Mean Squared Error (MSE) of 2.7494E-09 indicated a level of error that can be considered practically negligible. This exceptional performance demonstrated the capability of the neurologic solver algorithm to generate highly precise and reliable outcomes.

Furthermore, the subsequent evaluation focused on assessing the regression performance of the neurologic solver. This analysis aimed to determine the solver's ability to accurately detect and interpret signals from sensors, enabling it to make precise control decisions. Figure 6 visually presents the performance of the neurologic solver in this regard.

The regression analysis involved comparing the predicted values generated by the neurologic solver with the actual sensor signals. By measuring the degree of correlation between the predicted and actual values, the regression performance of the neurologic solver was assessed. A high degree of correlation would indicate that the solver effectively captured and interpreted the sensor signals, leading to accurate control decisions.

The results obtained from this evaluation provided crucial insights into the efficacy of the neurologic solver in detecting sensor signals and making precise control decisions. The close alignment between the predicted values and the actual sensor signals depicted in Figure 6 demonstrated the solver's ability to effectively analyze and interpret the data. This robust regression performance further substantiated the reliability and accuracy of the neurologic solver algorithm in the context of the SIS application.

Overall, the combination of minimal error indicated by the MSE analysis and the strong regression performance showcased in Figure 6 reinforced the effectiveness of the neurologic solver algorithm. These results contribute to the overall confidence in the neurologic solver's ability to accurately process sensor signals and enable precise control decisions, thus enhancing the reliability and performance of the system.

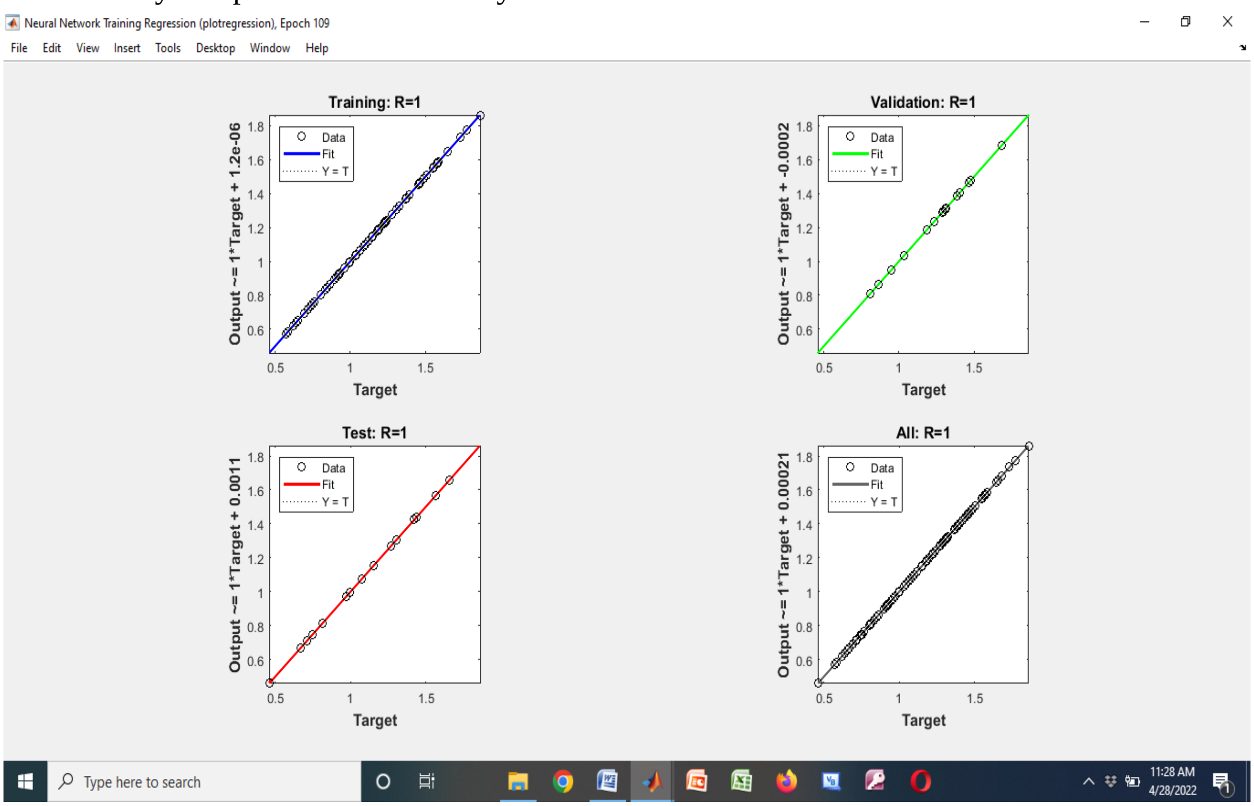

Figure 6: The Regression results

Figure 6 presents the regression performance of the neurologic solver. The aim here is to achieve a regression approximately or equal to one. The result here showed that the regression for the neurologic solver is 1, which implied reliability in controlling the tank overflow when error occurs in the process control section. To measure the failure rate of the neurologic solver, the neurologic solver was tested at operating time of 500hrs and the result presented in figure 7;

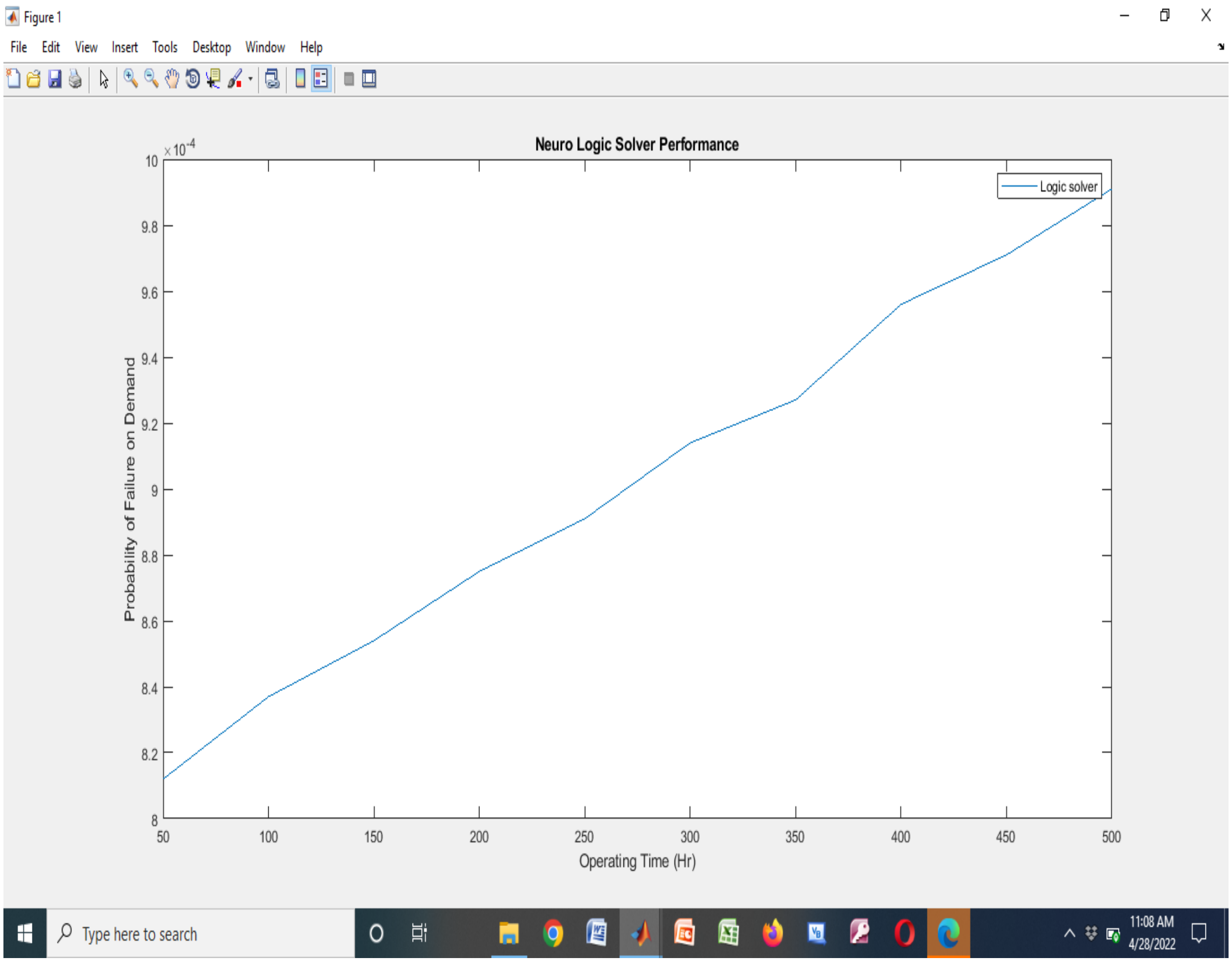

Figure 7: The neurologic solver PFD

Figure 7 presents the PFD of the neurologic solver using the PFD model(Stein et al., 2010) to identify the failure of the neurologic solver over 500 hours of operation time. From the result, the PFD is 9.14E-04. This PDF shows that the neurologic solver has a SIL of 4 when referred to the IEC standard.

5. Results of Neuro SIS with the Recursive Polynomial Estimator

This section presents the performance of the neuro SIS with the recursive polynomial estimation algorithm developed for the estimation of error in the system performance. The result showed the error identification of the SIS as ARMAX according to the equation 1 with the equivalent polynomial regression (which contained the white noise as the simulated error) as in figure 8

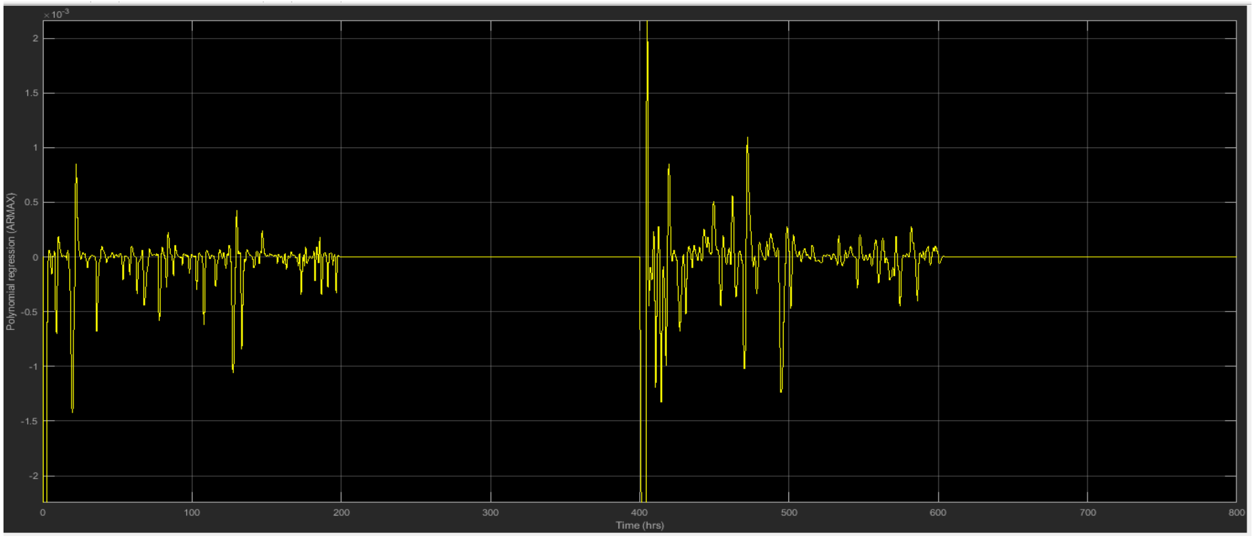

Figure 8: The SIS error identification result

Figure 8 provides a visual representation of the system identification results obtained from the polynomial estimation model. The purpose of this model is to accurately determine and understand the behaviors exhibited by the Safety Instrument System (SIS) plant. By employing a polynomial regression transformation, the model can effectively capture and represent the underlying patterns and dynamics of the SIS plant.

The process of system identification involves analyzing the input-output relationship of the SIS plant and extracting relevant information from the collected data. The polynomial regression transformation, as defined in equation 2, serves as a mathematical framework for mapping the input signals to the corresponding output responses. This transformation enables the model to capture the complex relationships and non-linearity inherent in the SIS plant's behaviour.

Figure 10 showcases the application of the recursive polynomial function in predicting the step ahead error of the signal. This function plays a crucial role in estimating the error that may occur in future time steps. By leveraging historical data and the identified polynomial model, the recursive polynomial function can forecast the potential deviations or discrepancies between the expected and actual signal values.

The ability to predict the step ahead error is of great significance in ensuring the robustness and reliability of the SIS. It enables proactive measures to be taken in response to potential errors or anomalies, thereby preventing system failures or hazards. By continuously monitoring and analysing the predicted errors, appropriate corrective actions can be implemented in a timely manner to maintain the optimal performance of the SIS.

Overall, the utilization of the polynomial estimation model and the recursive polynomial function facilitates a comprehensive understanding of the SIS plant's behaviours and enhances the system's ability to identify and address potential errors. This contributes to the overall reliability, safety, and effectiveness of the SIS in critical operational environments. The figure 9 presents the step ahead error prediction.

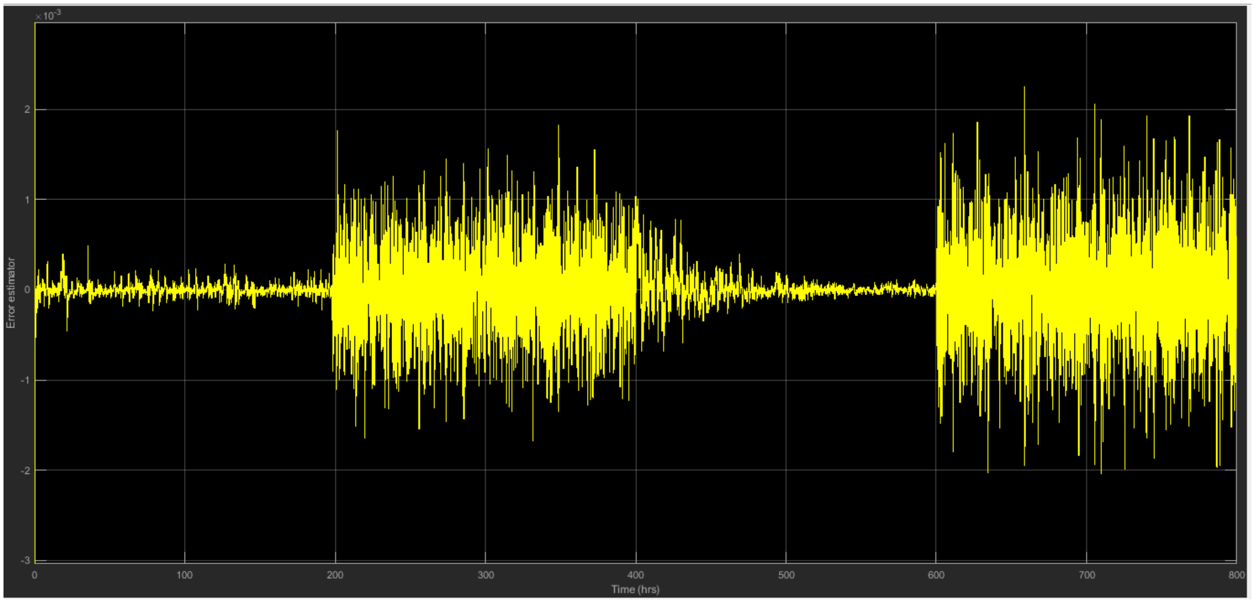

Figure 9: The Step ahead Estimated Error

Figure 9 present the step ahead error predictor of the SIS. From the model, the error in the SIS was estimated with equation 4 while the controlled output to stabilize the plant is presented in figure 10;

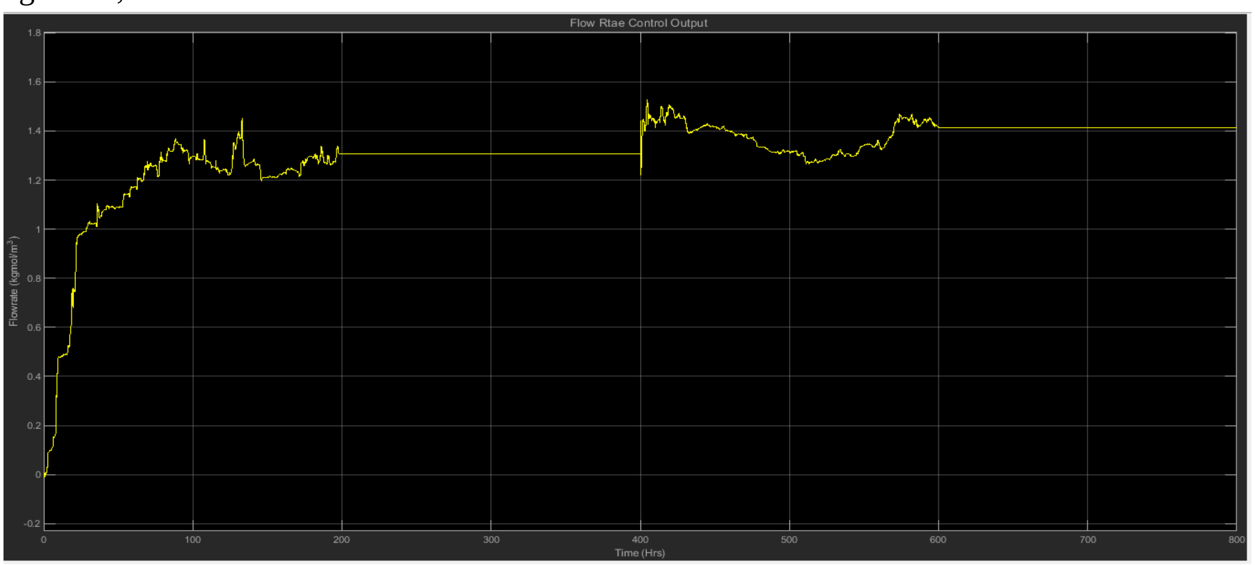

Figure 10: The Control output

Figure 10 provides a graphical representation of the control output of the plant, highlighting the significant impact of identifying and estimating errors ahead of time. By utilizing the neurologic solver algorithm and the error estimation techniques, the system was able to proactively identify and address potential errors, thereby minimizing the probability of system failure.

The integration of the neurologic solver algorithm allowed for the timely detection and estimation of errors in the system. This enabled proactive measures to be taken to mitigate the identified errors and ensure smooth and reliable system operation. As a result, the control output of the plant depicted in Figure 10 demonstrates a notable reduction in potential failures and an overall increase in the safety integrity level of the system. The ability to identify and estimate errors ahead of time provides a crucial advantage in terms of system reliability and safety. By addressing potential issues before they can escalate, the likelihood of system failure is significantly reduced, thereby enhancing the overall performance and integrity of the system.

The findings presented in Figure 10 highlight the positive outcomes achieved through the implementation of the neurologic solver algorithm and the error estimation techniques. By effectively managing errors and optimizing the control output of the plant, the system's reliability is greatly enhanced, and the safety integrity level is elevated. Overall, the utilization of these advanced techniques enables the system to operate with greater efficiency and resilience. The reduction in the probability of system failure demonstrated in Figure 10 reflects the successful implementation of proactive measures, ultimately leading to improved safety, increased reliability, and enhanced overall system performance.

6. CONCLUSION AND RECOMMENDATIONS

Safety integrity level of SIS cannot be zero due to the probability of failure on every engineering component or system. However, there are acceptable tolerance standard recommended which will guarantee optimal safety, but the available system used in the process design, control and SIS designs in our oil and gas industries today, despite the high risk involved in the technical process cannot reduce the risk to the tolerance level of 4 or 3 as the risk reduction factor. This has remained a major challenge and a problem waiting to be addressed as many lives and equipment are at risk when this system eventually fails; not mentioning the level of environmental hazard it will cause. There is need for SIS which will reduce this risk to the acceptable limit and ensure safety of lives and equipment. The benefit of solving this problem is an improved confidence of staff during technical process and ensuring that the system functions at optimal level during the fractional distillation and other processes. This paper successfully enhances the reliability of critical safety instrument systems through the integration of mathematical methods and machine learning techniques. The machine learning algorithm utilizes neural networks to develop a crucial component of the safety instrument system, known as the logic solver. On the other hand, a mathematical method involving a recursive polynomial estimation algorithm is employed to construct a reliability assessment model for error estimation in the safety instrument system and the implementation of control measures.

To evaluate the performance of the developed algorithms, they are implemented using Simulink and assessed using various metrics such as Mean Squared Error (MSE), regression analysis, Probability of Failure on Demand (PFD), safety integrity level, and Risk Reduction Factor (RRF).

The results obtained from the neurologic solver indicate an MSE of 2.98E-09, regression value of 0.9978, and a PFD of 9.00E-04. Upon integration of the neurologic solver on the testbed, the PFD decreases to 8.52E-04, corresponding to a safety integrity level of 4. In comparison, the testbed with a neuro PLC logic solver exhibited a PFD of 1.14E-03, representing a safety integrity level of 3. The overall PFD for the neuro-based safety instrument system is determined to be 6.44E-03, accompanied by an RRF of 155.279.

6.1 Recommendation for future

a) The study can be further improved considering other highly risk critical technical process plant other than distillation plant.

b) The solution proposed can be practically validated in further studies

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