Volume 3, Issue VII, July 2024, **No. 44, pp. 573-585**
Submitted 29/06/2024; Final peer review 11/7/2024
Online Publication 17/7/2025
Available Online at http://www.ijortacs.com

MODELING OF A NEURO-LOGIC SOLVER FOR IMPROVED RISK REDUCTION FACTOR IN PETRO-CHEMICAL INDUSTRY

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Abstract

This paper presents improving the reliability of critical safety instrument system using mathematical method and machine learning technique. 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, 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 risk analysis was done using inductive and deductive techniques which employed both fault tree analysis and self-defining equations to determine the probability of failure on demand (PFD) of the SIS components. 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.

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

1. INTRODUCTION

Chemical, petrochemical, gas compression, mining and many other types of manufacturing and industrial plant facilities can be very dangerous place to work in due to the high level of risk they pose. These risks include, fire hazard, tank overflow, gas release, chemical exposure or tank explosion, and as the daily demand for goods and services keep increasing, manufacturing companies are under lots of pressure to satisfy these demands and hence have increased technical process cycle, which proportionately increase risk and exposure of operators to hazards.

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. However, these measures alone cannot be relied upon to reduce the risk of fire, accidents explosion among other dangerous events which might occur as a result of fault to a level which is tolerable. Irrespective of the risk type, the process design, basic process control, alarm and operator engineer as layers of control only provides the first three levels of protection.

According to Durgut and Leblebicioglu (2016), each of these layers provide a tenfold safety better than the lower step. In order words, the process control provides tenfold more safety than the process design. The process design ensures the various control system equipment such as valves, pumps, plants are in the right system specifications. The Basic Process Control (BPC) systems are then installed with these appropriate devices, controllers and monitoring logics which allow the industrial plants to be operated within the safest ranges for temperature, pressure and flow rates of fluids. The alarms on the other hand are installed to alert the control system engineer of any nonlinear technical process, such as faults, overheating, excess concentration and pressure, so as to take necessary precautionary measures before the risks become an accident.

Nevertheless, even with these measures of protection in place, the risk may still be too great for an accident to be fully prevented from happening. For instance, in 2005, a plant explosion at the Texas oil and gas refinery killed 15 workers and injured 150 others. Recently in June 2020, the Philadelphia Energy solution refinery exploded and destroyed the alkylation unit where crude oil is converted to high octane gas (Susan, 2019). In the same month, Agence (2020) reported a plant explosion at the Nigerian refinery in Niger Delta, killing 7 workers and causing damages of equipment worth millions of naira. Another explosion occurred at the Florida chemical facility where lots of industrial properties were destroyed costing millions of dollars (Amanda, 2020a). Most recently in November 2020, 2 people were killed as a result of reactor explosion in the Indian pharmaceutical company (Amanda, 2020b; Nana 2020). In the same month, 2500 people were affected and 3 deaths recorded due to the explosion at the Baghjam Indian oil field (Guardian Times; 2020).

All these industrial facilities characterized with these fatalities, have process control systems, alarms and trained engineers; but these three levels of protections did not reduce the risk of accident to a level that is tolerable. This is because, sometimes in the process control design, systems which are meant to monitor the technical process might not consider some variables which will lead to accident. For instance, the alarm can easily malfunction without the knowledge of the operator engineer and hence will not notify threat when detected. The logic solver might fail to activate the sensors or control valve when overflow is detected. These as a result have become a major challenge and hence require a more reliable approach to address these risks and minimize accident occurrence to the lowest level.

To achieve this, the Occupational Safety and Health Administration (OSHA) and several companies in the chemical, oil and gas industries with other professional groups like the International Electrochemical Commission (IEC), embraced the idea of defining risks as associated with general technical process function and then developed the ISA84 and IEC61508 as a standard for the concept of industrial safety. These standards were later harmonized into a single signature as ISA-84/IEC-61511 which leads to the need for an extra well designed safety measure called the Safety Instrumented System (SIS) (Marvin, 2016).

This SIS is presented as an additional layer of protection above the first three layers already pointed out. This layer is expected to provide an additional tenfold protection with a Risk Reduction Factor (RRF) of equal to or greater than 10 (Realpars, 2017). This is to say that each of the levels of protection like the process design, process control, alarm, and now SIS provides a tenfold RRF better than the other. That is, each level of protection is not only required by operation to reduce industrial risk hazards to a tolerable level, but must be determined by each individual company. To help achieve this, the standard has provided benchmarks for various industries like the oil and gas, food and beverages, chemical industries among others, depending on the level of risk they possess, called Fatal Accident Rate (FAR) which is a standard way of measuring overall risk.

SIS is a system composed of control valves, logic solvers, sensors, transducers and final control elements which are designed to take the technical process to a safe state when predetermined nonlinear conditions are violated. This SIS is defined using a Safety Instrumented Function (SIF) which specifies the exact control function the SIS is expected to activate, when fault is sensed (Mohamed et al., 2007). However, despite the improved risk reduction factor offered by the SIS, it also has a Probability of Failure (POF). The POF can occur due to technical challenges like sensor faults, faults from the isolation valves, even the logic solver not responding when expected and are called independent failures, then all or some of the components can fail simultaneously due to common cause problem (Eke and Eneh, 2007).

Failure can be very dangerous when all components fails or when critical components without redundancy like the logic solver fails. This can be very catastrophic and fatal when it occurs and hasto be drastically reduced from happening. The conventional Programmable Logic Controller (PLC) based logic solver can easily fail today due to the many technical problems like communication error, memory loss, processing error, module failure, problem of oscillation, etc. (Cory, 2013; Yuvraj, 2012; Cauffriez et al., 2014). This technical problem presented the lack of integrity and reliability on the conventional SIS system and hence presents the need for optimization.

This paper therefore presents the development of a machine learning based logic solver algorithm which will reduce the risks identified in the conventional PLC based logic solver system, then an error estimation model which will monitor and perform critical reliability assessment on the SIS will be developed using recursive polynomial function.

2. RESEARCH METHODOLOGY

The methodology used 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 analysed and compared with the characterized testbed for percentage improvement.

2.1 Data Collection

Having successfully performed the risk assessment test on the SIS, the data was collected considering the Probability of Failure on Demand (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 analysed 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.

3. MACHINE LEARNING BASED LOGIC SOLVER SYSTEM

From the risk assessment test conducted, the PLC logic solver remains one of the most critical components of the SIS and it has no redundancy. This component is the coordinator of all control operation based on data collected from the sensors to ensure safety is achieved in the technical process and requires the most attention to reduce the failure probability to approximately zero. Other components like the final control elements which are the valves, the sensors such as the pressure and temperature sensors all have redundancy (if one fails, another can complement) and can operate in 1oo3 or 1oo2 modes respectively, however the logic solver which does not have redundancyis the most important components in the SIS need to guarantee functional safety.

To this end, 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 as shown in the figure 1;

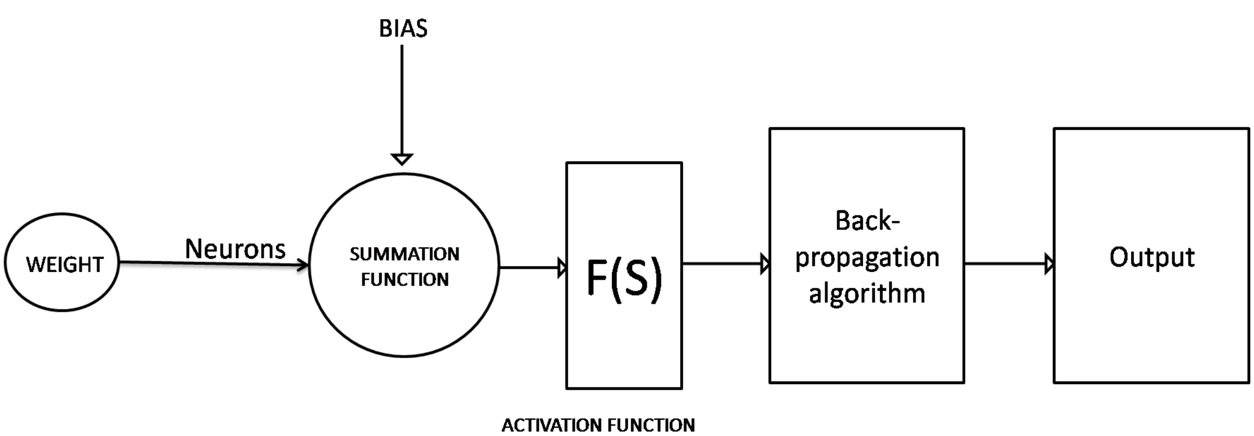

Figure 1: The neural network architectural model

The model showed 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 as shown in the flowchart of figure 2. The flowchart of the training algorithm is in figure 2

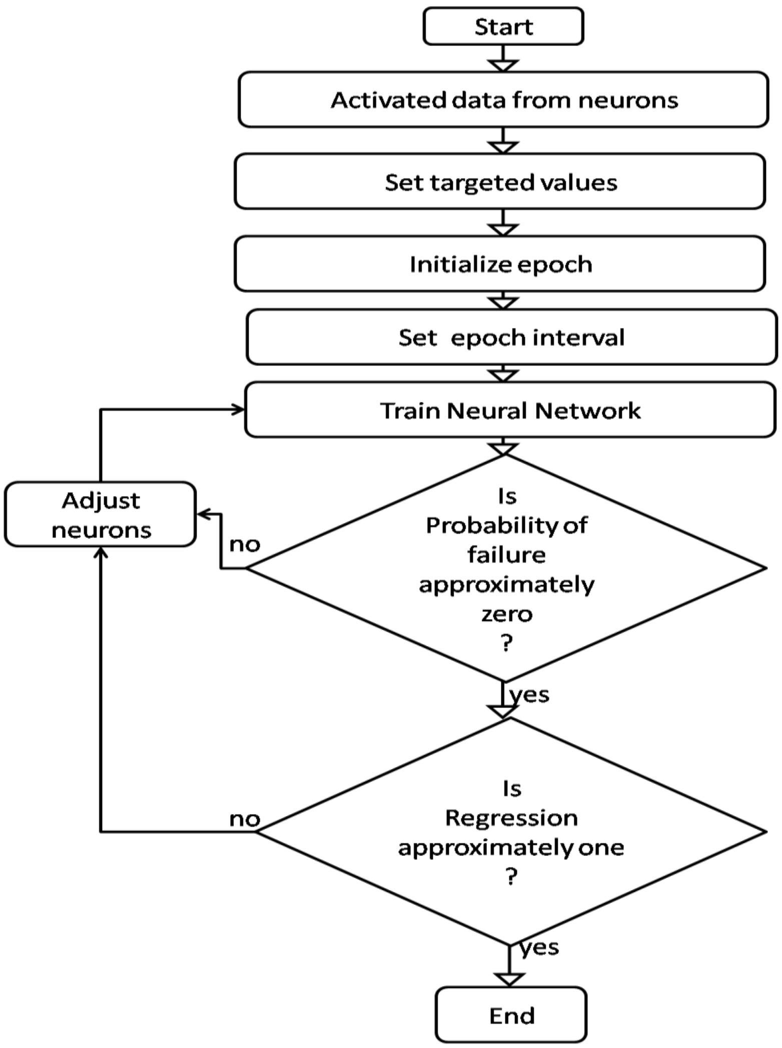

Figure 2: Gradient Descent Training Back-propagation Algorithm

The flow chart of figure 2 present the training algorithm used to train the neural network model in figure 1. To achieve this, the plant data was loaded into the neural network for configuration and training using the algorithm in figure 2. The neural network training model which shows how the neural network identified the loaded plant data and then train the neurons with the training algorithm presented above is shown in figure 3;

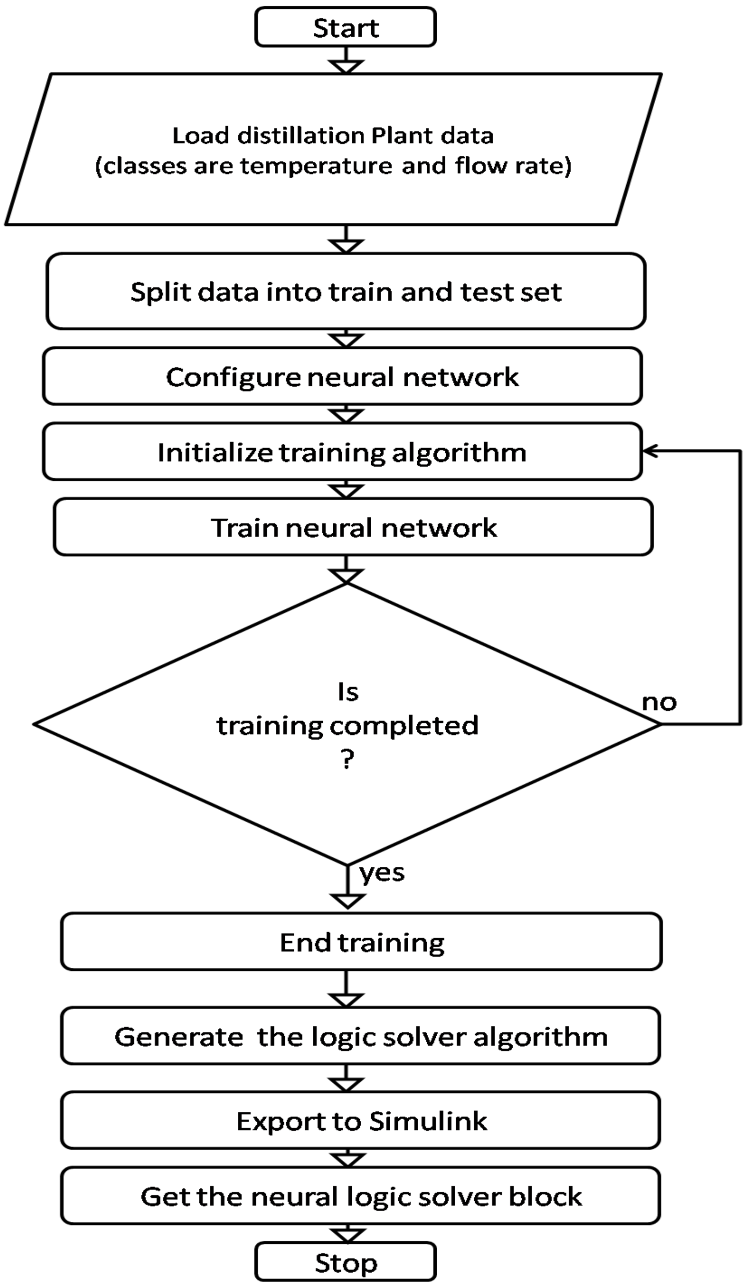

Figure 3: The neural network training model

Figure 3 present the flow chart of the neural network training process used in generating the neuro logic solver algorithm and hence the neural logic solver system Simulink, 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;

3.1 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
7) Failure probability ≈ 0
8) Generate logic solver algorithm
9) Else
10) Back-propagation
11) Adjust neuron
12) Repeat step (5; 6; 7 and 8)
13) Generate logic solver algorithm
14) Else
15) Do (step 13) until step 8 is true
16) Generate neurologic solver algorithm
17) Generate the neurologic solver block
18) End if
19) End if
20) 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.

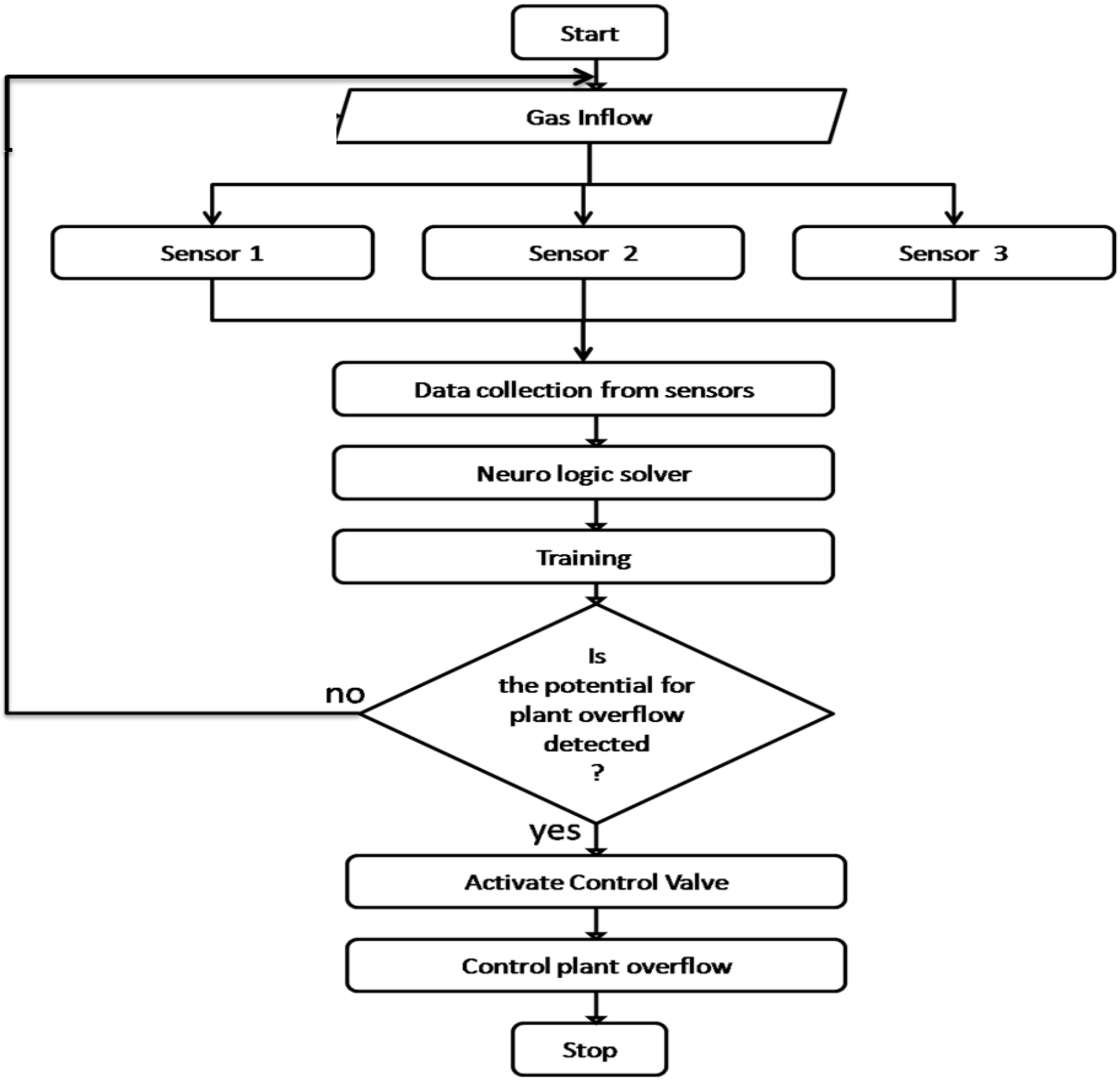

Figure 4: Flow chart of the neuro-based SIS operation

Figure 4 present the neuro-based SIS system which collect data from the temperature and pressure sensor and used to monitor the behaviour of the distillation plant for tank overflow when the process control logic solver fails. The SIS detects the problem and activates the control valves to stabilize the plant and prevent the problem. The system block diagram is presented in figure 5;

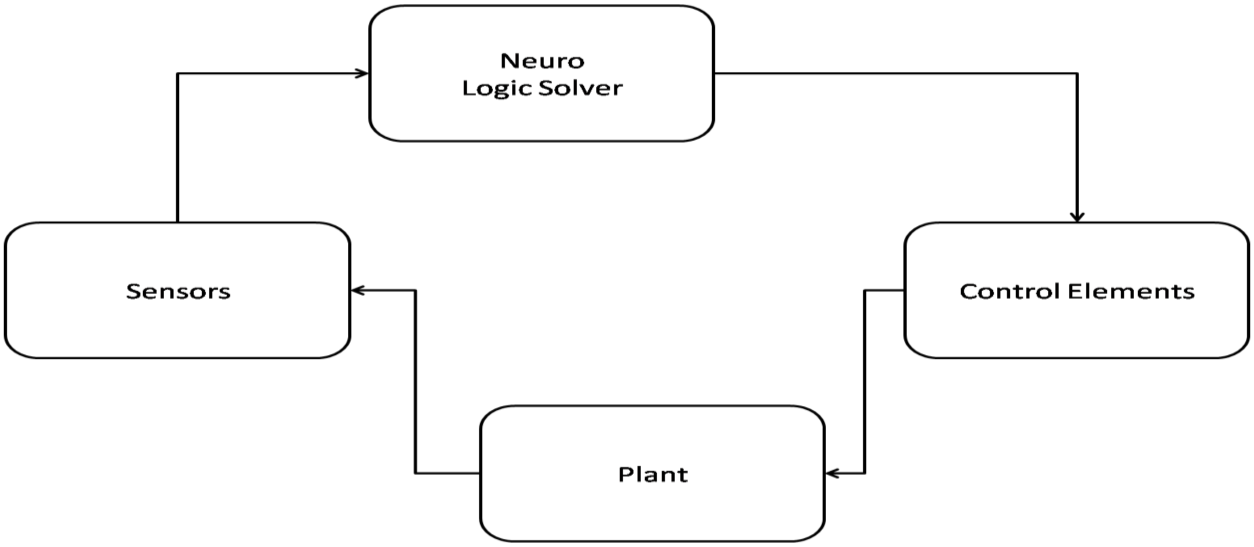

Figure 5: Block Diagram of the neuro-based SIS

The figure 5 shows how the plant behaviour was collected by the sensors and fed forward to the neuro-based logic solver algorithm which trains the data to detect the distillation plant overflow problem and then activate the final control element which are the valves to control the plant behaviour.

4. SYSTEM IMPLEMENTATION

The neuro-based SIS was developed using the models of the testbed which has the distillation plant, the sensors, the logic solvers and the final control elements. The study focused on the logic solver which was with many limitations and probability of failure due to common cause problems. Model of the new SIS was developed using artificial neural network as shown in figure 3 and the mathematical transfer function presented in figure 6;

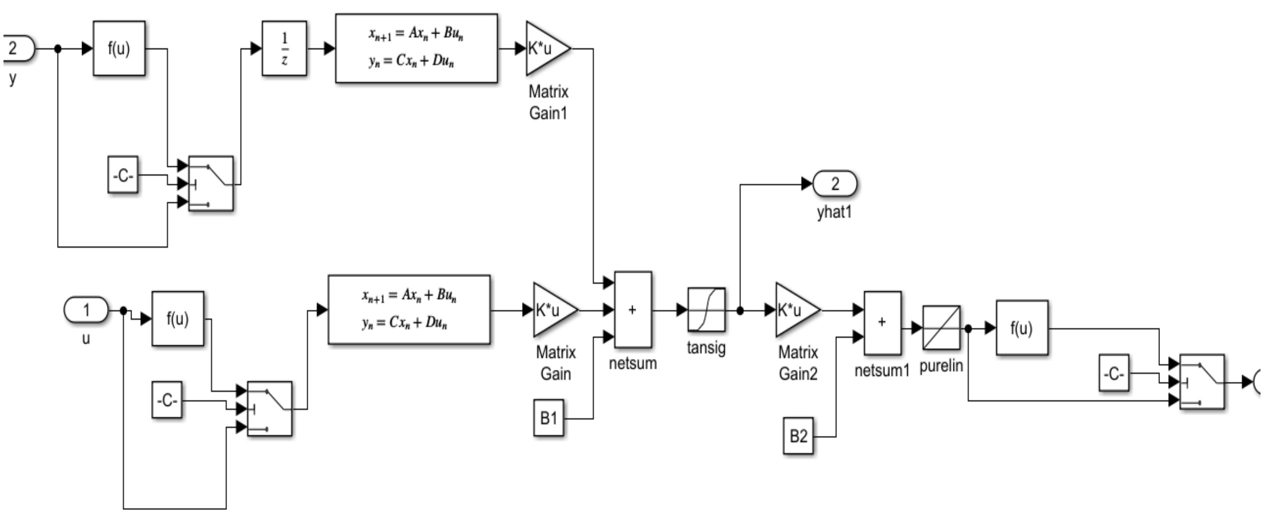

Figure 6: Simulink transfer function of the neural network

Figure 6 shows the neural network transfer function which represents the interconnection of the neurons with the activation functions and training algorithm to train the data of the distillation plant collected and generates the neuro logic solver algorithm.

5. RESULTS OF THE NEUROLOGIC SOLVER ALGORITHM

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 4 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 Agbaraji, 2015). The MSE performance were presented in figure 7;

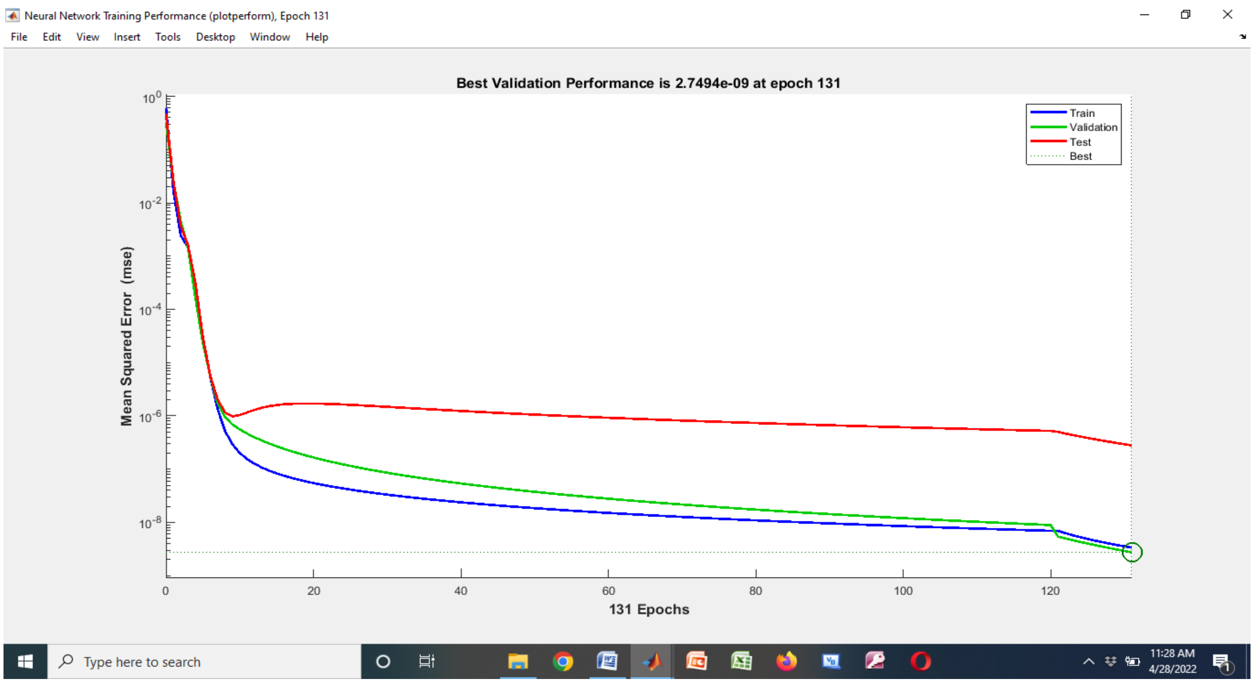

Figure 7: The MSE of the neurologic solver

The analysis of the results depicted in Figure 7 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 8 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 4.2 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 8 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.

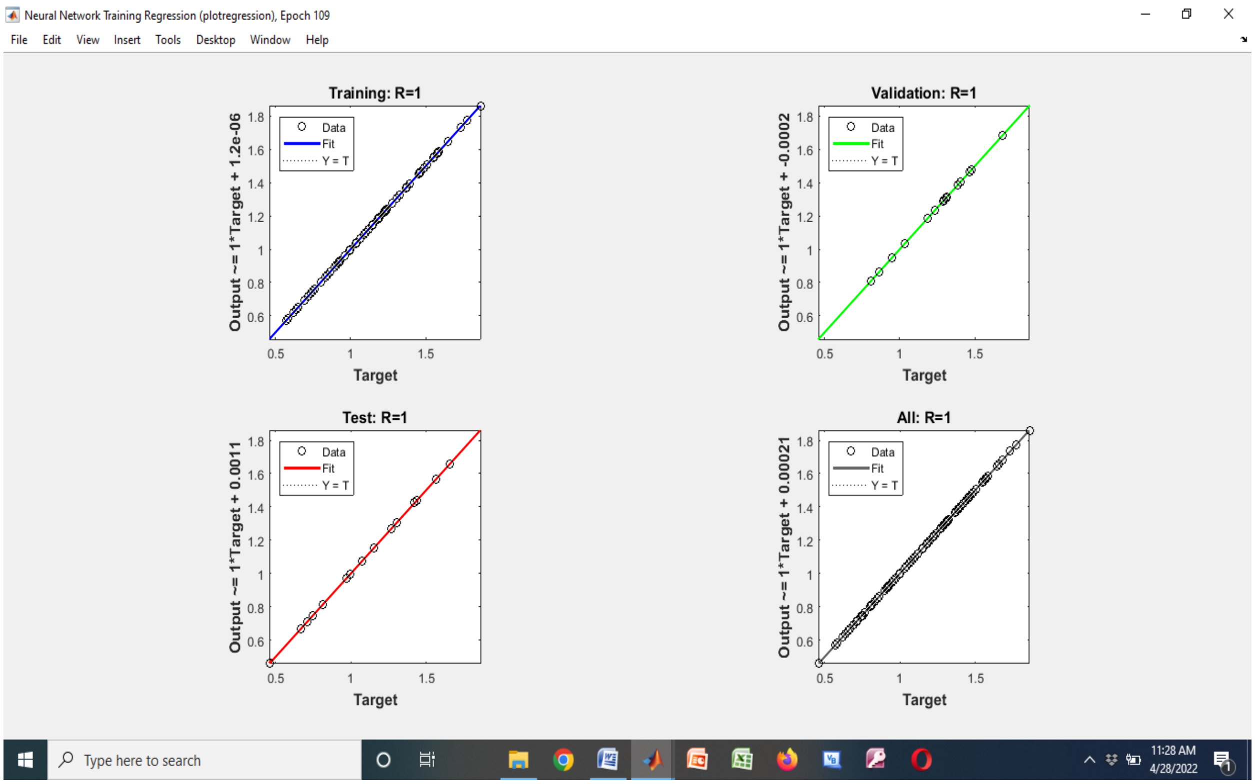

Figure 8: The Regression results

Figure 8 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 9;

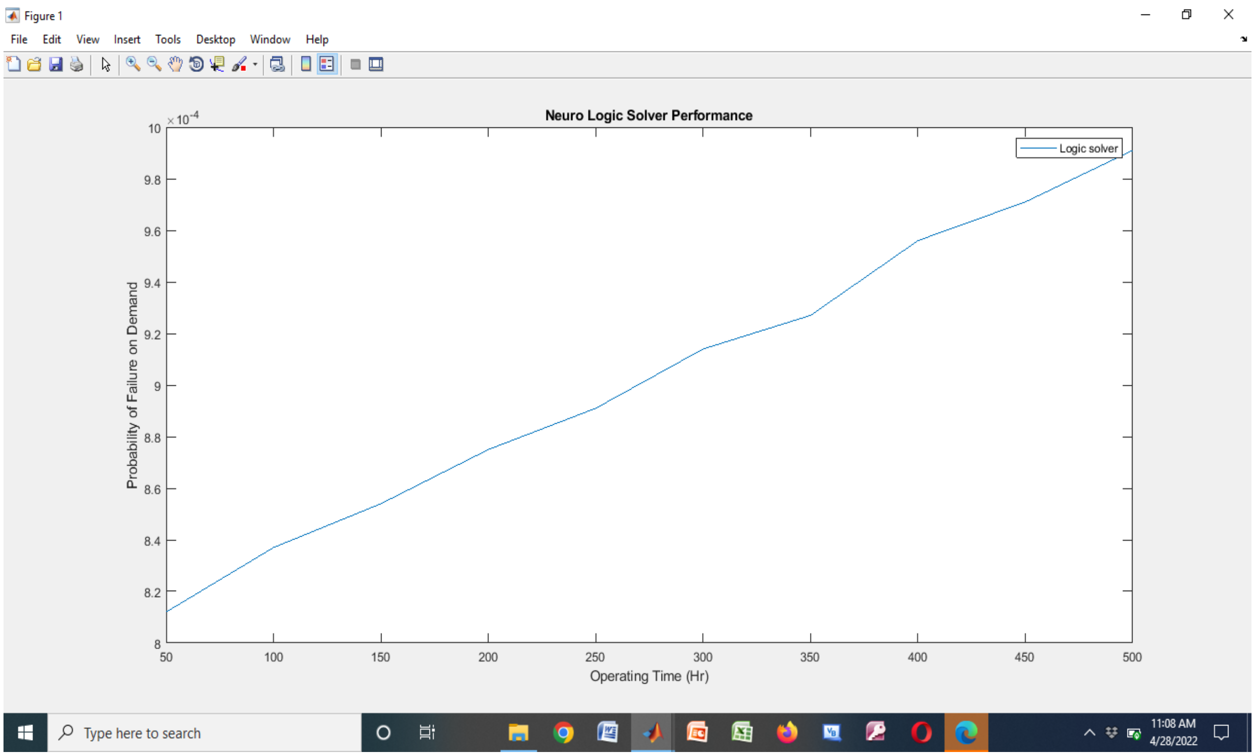

Figure 9: The neurologic solver PFD

Figure 9 presents the PFD of the neurologic solver using the PFD model(Innal et al., 2019) to identify the failure of the neurologic solver over 500 hours of operation time. From the result, the PFD is 9.14E-04. This PFD shows that the neurologic solver has a SIL of 4 when referred to the IEC standard. This section is part of solution for the performance evaluation objective.

6. CONCLUSION AND RECOMMENDATION

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. Furthermore, the analysis of the PFD, based on the IEC safety integrity table, reveals that the safety integrity level is upgraded from 2 (with PLC) to 3 (with neural network). These findings demonstrate that the neurologic safety instrument system and the developed mathematical model for error estimation effectively improve safety and restore reliability to the technical process.

6.1 Recommendation for future

1. The study can be further improved considering other highly risk critical technical process plant other than distillation plant.
2. The solution proposed can be practically validated in further studies

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