MODELLING OF REAL TIME FLOOD DETECTION AND CONTROL SYSTEM USING MACHINE LEARNING TECHNIQUE

Ebere Uzoka C[1], Eke James[2]

[1,2] Department of Electrical and Electronic Engineering, Enugu State University of Science and Technology, Enugu State, Nigeria.

Article Info
Received: 11/04/ 2023
Revised: 27/04/2023
Accepted 12/05/2023

Corresponding Author's Email:
cjeneral@yahoo.com

Corresponding Author's Tel:
+2348061163740

ABSTRACT

This paper presents the modeling of a real-time flood detection and control system using machine learning techniques. The experimental and simulation methodology was employed to achieve the objective of this work. The study characterized an existing flood detection system and identified the technical challenges after data collection and analysis, then a nonlinear flood model was developed, and a sensor was designed to acquire real-time flood data from the environment, considering volume and pressure an sensing elements. A nonlinear model predictive control system was then modeled using flood data, artificial neural network and implemented in Simulink, which utilized previous flood behavior to forecast the future response of the system. The simulation results demonstrated that the new flood detection system achieved a regression of 1 after several iterations, indicating a good fit between the model and the actual flood data. Overall, the results of this study indicate that the proposed flood detection and control system has the potential to effectively detect and mitigate floods in real-time, thus reducing the loss of life and property caused by flooding.

Keywords: **Keywords: Flood Detection; Non-linear Neuro Model Predictive Control; Machine Learning**

1. INTRODUCTION

The occurrence of floods is a major natural disaster that poses a significant threat to human life and property across the globe. Certain regions are more susceptible to flood disasters due to their proximity to water bodies and high rainfall rates (Sadhya and Shejina, 2021). Floods can be characterized as a situation where a large amount of water is present in an environment, and its flow becomes uncontrollable. Several factors contribute to the risk of floods, including heavy rainfall, deforestation, and rapid urbanization. Early flood detection and forecasting is essential to mitigate the loss of life and property during a flood. However, flood forecasting is a complex process that involves several parameters such as rainfall, river level, ground saturation, soil permeability, and localization of the system. Artificial intelligence techniques such as Artificial Neural Network (ANN), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), random forest, and Convolutional Neural Network (CNN) have been employed for automatic early detection and forecasting of floods (Sandhya and Shejina 2021; Abdirahman et al., 2021; Tibin et al., 2017; Joe and Alexander, 2019). Non-artificial intelligence techniques, such as the use of ultrasonic and pressure sensors in the environment, are also available to detect floods (Nalini et al., 2020). Researchers have attempted to solve the issue of floods in communities through publications, but limitations in the performance of the systems developed still exist (Nalini et al., 2020; Mousa et al., 2016; Abdirahman et al., 2021; Elizabeth et al., 2008; Sandhya and Shejina, 2021; Gadede et al., 2019). Therefore, this paper proposes the use of machine learning techniques for the early detection and forecasting of floods due to its high-power saving capacity, speed, and ability to learn from errors, and adaptability to different localization parameters.

2. METHODOLOGY

The methodology used for the development of the system is a combination of experimental and simulation methodologies. The experimental methodology was used for technical investigation, which involved studying existing flood detection and monitoring systems and developing the new model. The machine learning approach employed was the artificial neural network, which was used for modeling the new flood detection and control system, and then implemented to improve the performance of the system using the simulation methodology. To analyze the system, the standard of the Nigerian Emergency Management Agency (NEMA) was used, which classifies flood as occurring when water is 30cm above normal sea level.

This work characterized a Deluxe flood monitoring and detection system (testbed) at the National Emergency Management Agency (NEMA) Port-Harcourt, River State, Nigeria. The aim of the characterization was to study the flood detection system, identifying the technical challenges with it, and then improve the performance. The parameters considered for the characterization are water volume, height of the river and time. The figure 1 presented the setup used for the characterization process.

2.1 Characterization of flood detection system

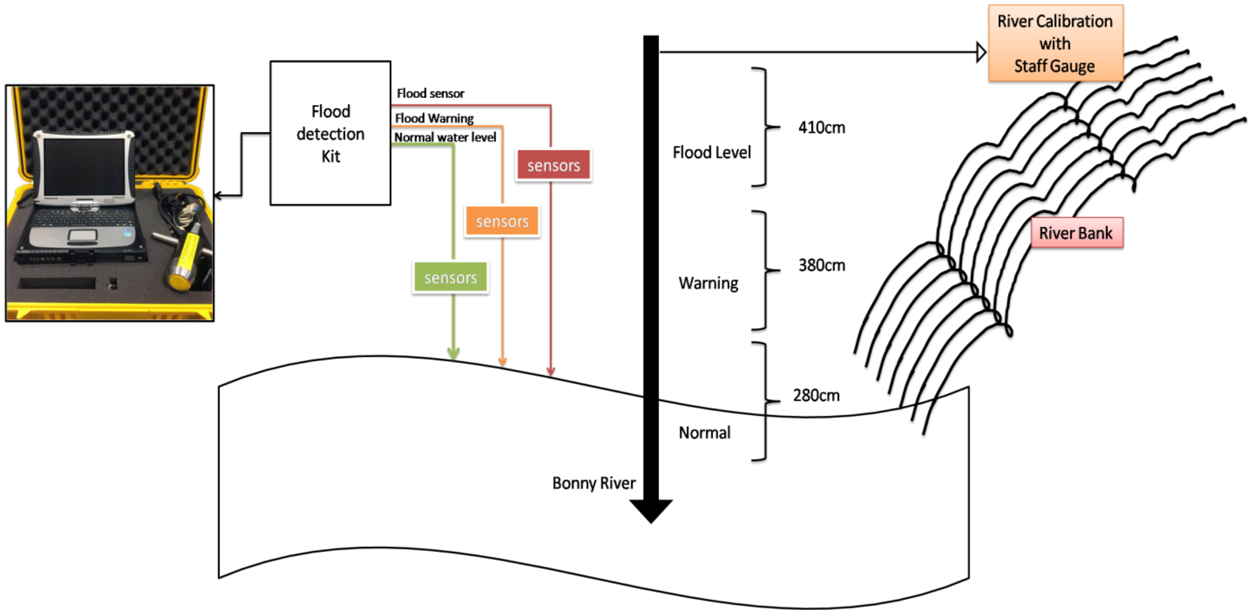

Figure 1: The test setup

The method used for characterization is the experimental method. To perform the characterization process, first, the staff gauge was used to measure the height of the river with respect to the river bank to determine the stages where water level is normal, needs a warning, and needs an evaluation alert due to the pending flood event. This was done before the flood, precisely on 2nd February 2021. The next phase of the characterization process took place on 19th August 2022 during the flood event, which claimed many lives and properties in the case study area. The steps used for the investigation involved three sensors, each attached with colored indicators representing the level of water at a given height in the river, which were used for data collection. These sensors were attached to a gauge staff and then positioned at the riverbank. The sensor with the green indicator was used to monitor and collect data of normal river flow. The sensor with the yellow indicator was used to monitor and detect a warning flood signal, while the sensor with the red indicator was used to collect data of early flood and signal for immediate evacuation. The location of the sensor was strategically positioned at the riverbank based on the calibration of the river height performance using the staff gauge instrument. After the data collection, the laptop on the flood kit, which was already installed with Harus software, was used to interpret the water level and save readings for analysis. Readings were taken every 5 seconds in 37 timestamps. The interval in time was to ensure that the behavior of the river was properly captured as a river presents a nonlinear time-invariant system; hence the actual behavior can only be captured in varying time spans. The indicators were also used to monitor the water level and indicate key levels, which represent normal water level, less than 100 cm, flood warning level, which is between 101 and 380 cm, and the actual flood level, which is above 420 cm, or 30 cm above sea level. All data collected from the experiment were presented for analysis in Table 2.

3. SYSTEM MODELLING

This section presented the model of the system development. The model developed is the model of the nonlinear river behaviour which presents the flood model, model of the sensing element and model of the flood prediction system. The figure 2 presented the structural model of the flood as;

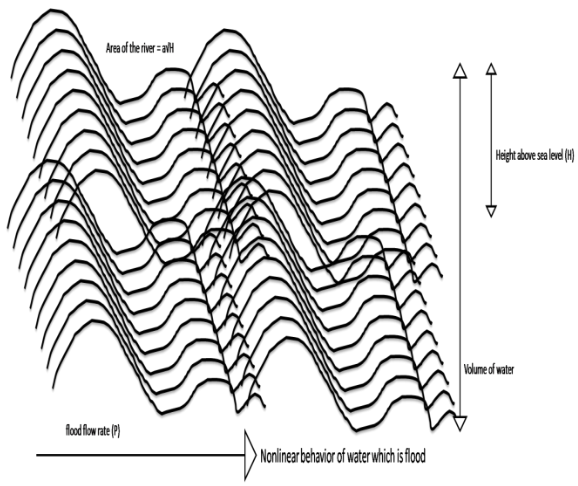

Figure 2: the structural model of the river

The figure 2 models the river dynamics, showing how water from various drainage systems flows into the river proportional to pressure P. The river when overflowed spilled through the environment at a rate that is proportional to the square root of the water height, H, of the river. The presence of the square root in the water flow rate makes the river nonlinear.This is represented using the differential equation 1 (Mumu and Yadav, 2012);

$$\frac{dV}{dt} = A; \frac{dH}{dt} = bP - a\sqrt{H} \qquad 1$$

Where H is the river height above sea level; V is the volume of the water flow; P is the applied pressure of water flow rate; A is the cross-sectional area of the river; b is the flow rate constant into the river; a is the flow rate constant out of the river.

3.2 Sensor model

In developing the model of the flood sensor, pressure is very important to consider as a key factor in the system design, this is to help differentiate flood from erosion. The two natural phenomena's involves water spillage; however that of flood involves high pressure (Mumu and Yadav, 2012).The sensor is designed using a logic gate which considers water and pressure as the input signal. The sensor model is developed using the flow chart in figure 3.

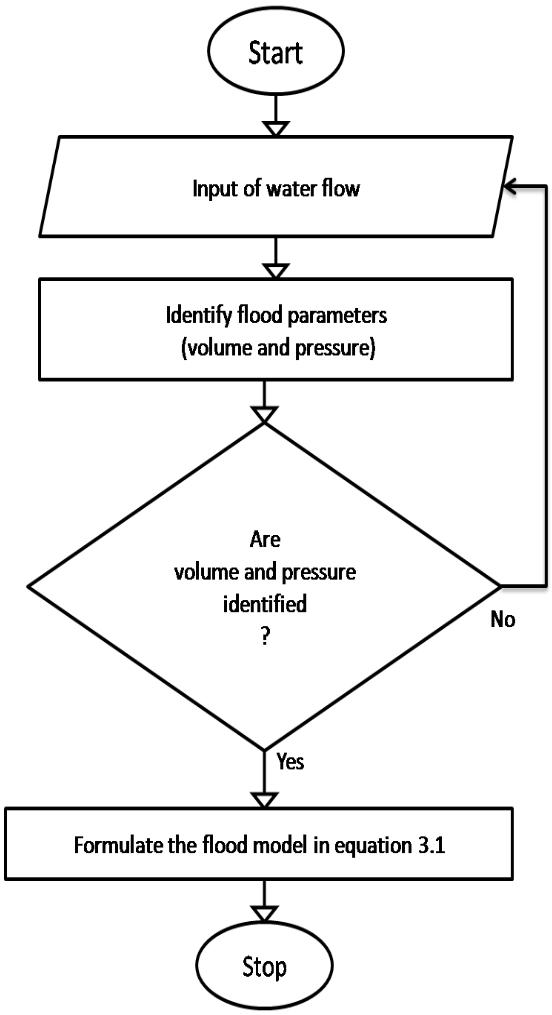

Figure 3: flow chart of the flood sensor

3.3 Sensor calibration

This is the linear relationship between the sensor output and the height of the river. This is determined by considering the volume at varying height (X inches) and then measuring the sensor differential output Y, given that (Mumu and Yadav, 2012);

$$Y = Vwater + Vpressure \qquad 2$$

Then sensor is then calibrated using the linear relationship which considers the two parameters as shown in the structure below;

International Journal of Artificial Intelligence Trends (IJAIT)
Vol. 2, Issue 5; No. 46, May, 2023, pp. 488-498

$$\Delta Vsensor = \frac{\Delta y}{x}\ x\ Height \quad 3$$

The linear relationship can be employed to find the sensor's differential output ΔVsensor at the new height. The logic circuitry in figure 4, presents the internal logic architecture of the sensor with the truth table in table 1.

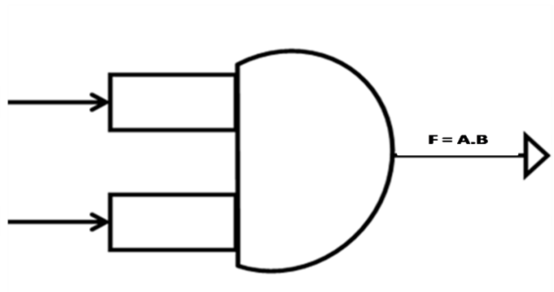

Figure 4: logic circuit for the sensor model

Table 1: Digital logic AND Gate for the logic circuitry

A	B	OUTPUT
0	0	0
0	1	0
1	0	0
1	1	1

3.4 Nonlinear Neuro model predictive Control (NNMPC)

This is an artificial intelligence technique that employs a control strategy adopting the model of the system (plant) in order to make next prediction on which an optimal input sequence is determined, so as to minimize an objective function not neglecting Constraints. The basic components for the process are (Toni et al., 2010);

- The process model which combines the non-linear state space model rainfall model input of rainfall in order to predict the future output within a predetermined (objective function) volume and height.
- The objective function is minimized taking into account constraints on the input and output as a quadratic function, trying to minimize the deviation of the water level with the reference level and the rate of increment in volume (in this case with artificial neural network).
- Model of the neuro predictive Controller (NPC)
- Training of the plant with the NPC to obtained an improved neuro sensor

3.5 System identification

This process identified the nonlinear flood model of the logic output (plant) as a nonlinear auto regressive model using the structure below

$$y(k+d) = N(y(k), y(k-1), \dots, y(k-n+1), u(k), u(k-1), \dots \dots u(k-n+1)) \quad 4$$

Where u(k) is the feature vectors inputs, N is the non-linear slip force, and y(k) is the system output as shown using the neural network architecture in figure 5.

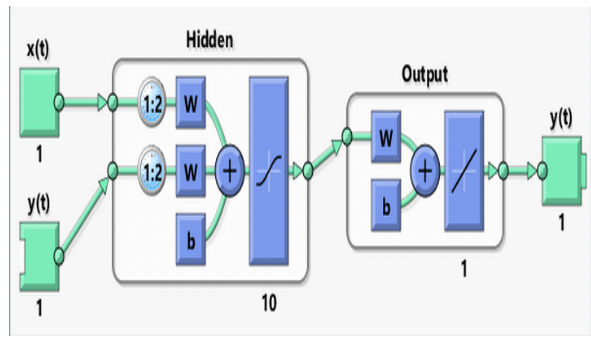

Figure 5: neural network model

3.6 Neural Network Training

Considering the nature of the dynamic model identified, the BFGS quasi-Newton back propagation algorithm was used to train the model. The algorithm was used to calculate derivative of performance with respect to the weight and bias variables x. each variable is adjusted according to the following

$$X = X + a * dx \quad 5$$

Where dx is the search direction, the parameters a is selected to minimize the performance along the search direction. The line search function is used to determine the minimum point. The first search direction is the negative of the gradient of performance. In succeeding iterations, the search direction is computed according to the following formula;

$$dX = -H\backslash gX \quad 6$$

Where gX is the gradient and -H is an approximate Hessian matrix. The training stops when any of these conditions occurs. The maximum number of epochs (repetitions) is reached; the maximum amount of time is exceeded; Performance is minimized to the goal; Precision problems have occurred in the matrix inversion. The training algorithm was presented in figure 6;

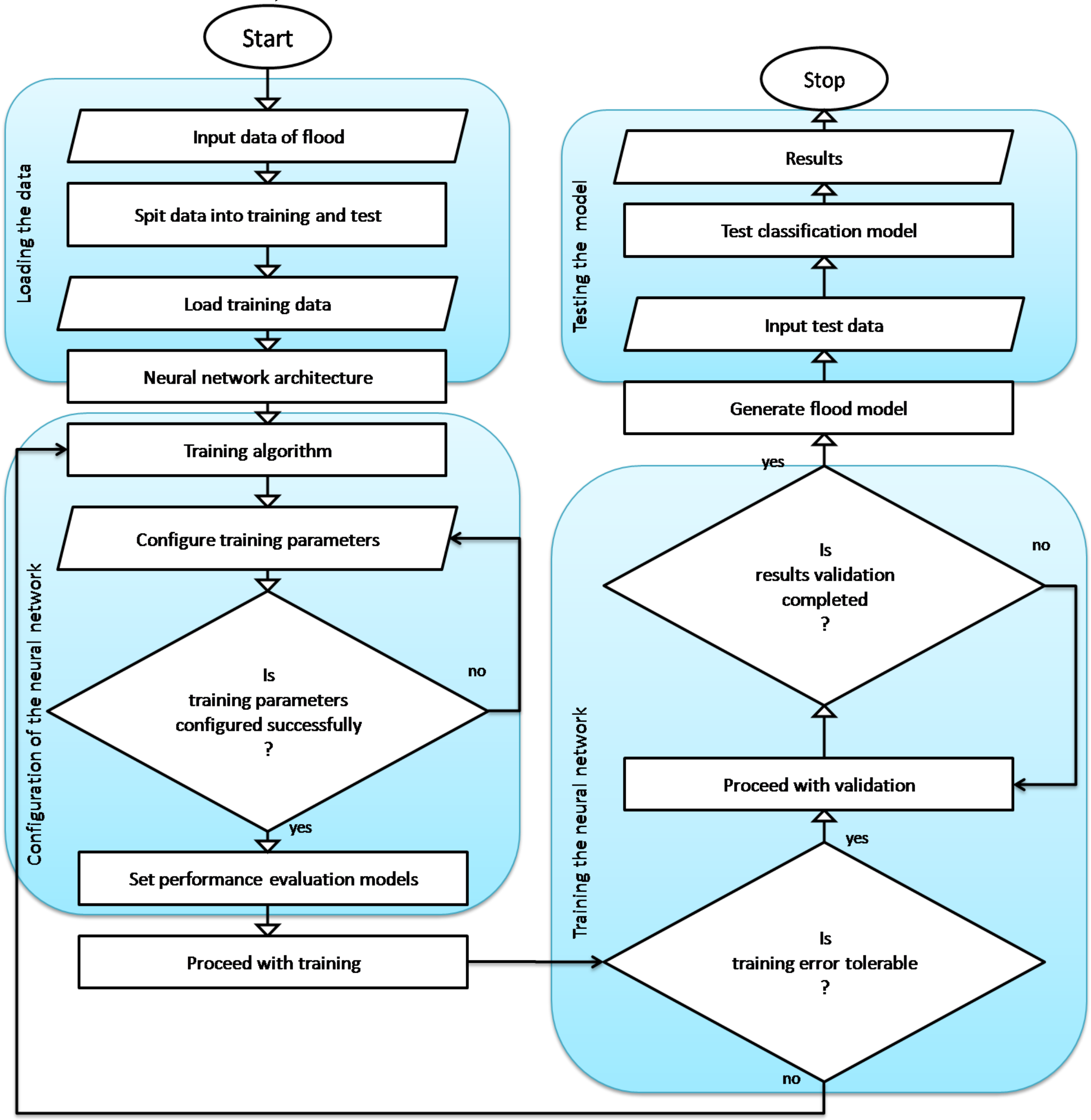

Figure 6: Flowchart for ANN Training

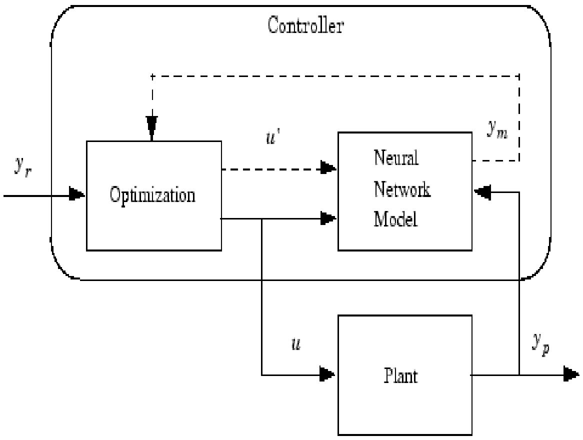

Figure 7: block diagram of the Neuro controller

The figure 7 presents the block diagram of the neuro controller. The result showed that the plant input was feed to the neural network which used the optimization algorithm (back-propagation) to train and generate a reference output y_r which used the controlled input u' to solve the nonlinear problem of y_r. During the training, when the errors y_m were feedback to the optimization algorithm and train until the neurons learn the data and generate the neural network controller as in the Simulink of figure 8;

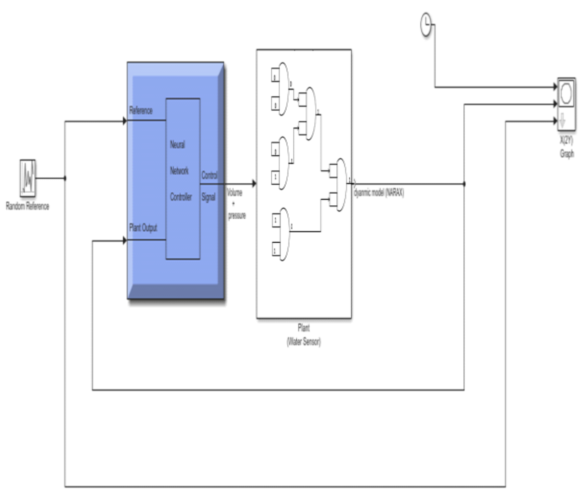

Figure 8: Simulink model of the neuro sensor

4. RESULTS AND DISCUSSIONS

This section presents the result of the technical investigation performed on the existing flood detection and monitoring system. The investigation considered parameters such as the time of flood, water flow rate, sensor response and status which interprets the sensor behavior at very time stamp and related with the models in equation 1. The data collected was presented in the table 2;

Table 2: characterization result (Source: NEDI)

Time interval (sec)	Flood level (cm^3/h) with PID-FL	Status
5.0	93.8	Green Alert
10.0	91.8	Green Alert
15.0	86.9	Green Alert
20.0	88.5	Green Alert
25.0	90.5	Green Alert
30.0	92.9	Green Alert
35.0	95.8	Green Alert
40.0	97.6	Green Alert
45.0	98.7	Green Alert
50.0	98.9	Green Alert
55.0	99.9	Green Alert
60.0	98.92	Green Alert
65.0	99.98	Green Alert
70.0	100.5	Green Alert
75.0	101.8	Green Alert
80.0	111.8	Green Alert
85.0	117.5	Green Alert
90.0	164.6	Green Alert
95.0	173.5	Green Alert
100.0	174.9	Green Alert
105.0	185.4	Green Alert
110.0	228.6	Green Alert
115.0	311.0	Yellow Alert
120.0	249.1	Yellow Alert
125.0	355.3	Yellow Alert
130.0	357.4	Yellow Alert
135.0	363.9	Yellow Alert
140.0	413.3	Red Alert
145.0	458.9	Red Alert
150.0	457.1	Red Alert
155.0	454.8	Red Alert
160.0	449.8	Red Alert
165.0	439.8	Red Alert
170.0	434.3	Red Alert
175.0	443.1	Red Alert
180.0	445.7	Red Alert

The table 2 presented the result of the characterization performed on the flood detection system with PID at the NEDI center. The result showed the data collected using the sensor and how it was able to read flood from the water level changes. To analyze the result obtained, the figure 9 was used which considered the flood when the water level rises over 10cm above the normal sea level and then control.

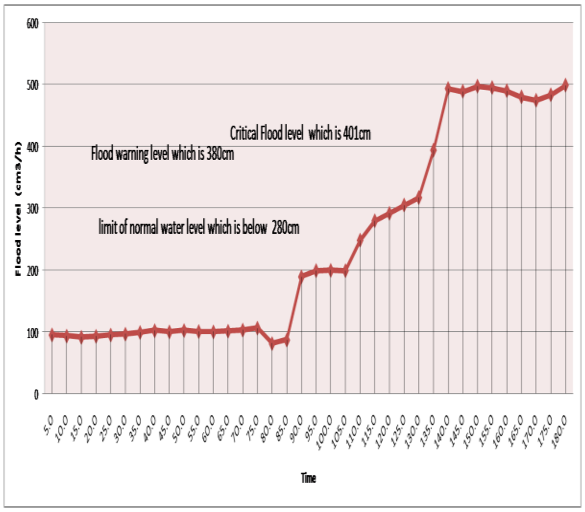

Figure 9: Graph of the flood detection result with PID

The figure 9 showed the performance of the flood detection system characterized. The result showed that when water level rises over 280cm, the system sends warning signal and notify the environment of early flood warning. When the water level rises 10cm above the NEMA requirement for worst case scenario for normal sea level, then the system notifies for flood. To analyze the step response performance o the flood detection system and read out the technical challenges which justified the new solution is presented in figure 10;

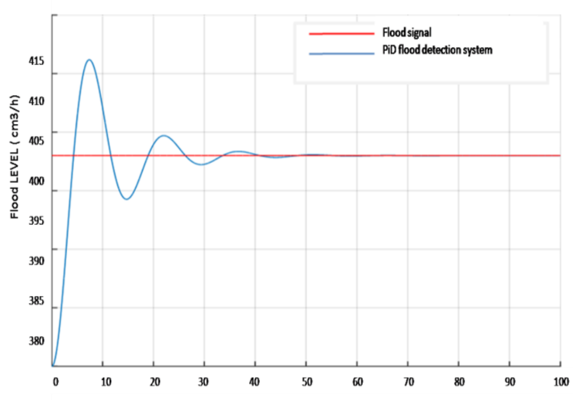

Figure 10: Step response of flood detection system with PID

The figure 10 presented the step response performance of the characterized flood detection and monitoring system. The result showed that the during flood event, the flood detection and monitoring system with PID (PID-FL) detected the signal at 5s and then sends notification after 41.7s as against the 10.4s recorded in the new system developed with neural network. The implication of the result showed that the PID-L despite the success suffers develops time to notify for flood. The tie might seem relatively low, the impact of flood on environment, human lives, etc within the specific time can take a whole live time to recover, hence there is need to optimize the control response and take necessary measures fast to prevent the disaster.

4.1 Training ANN Results

From the neural network training, there is need to analyze the error between the input and output of the training process. This is evaluated using the mean square error evaluation graph of figure 11;

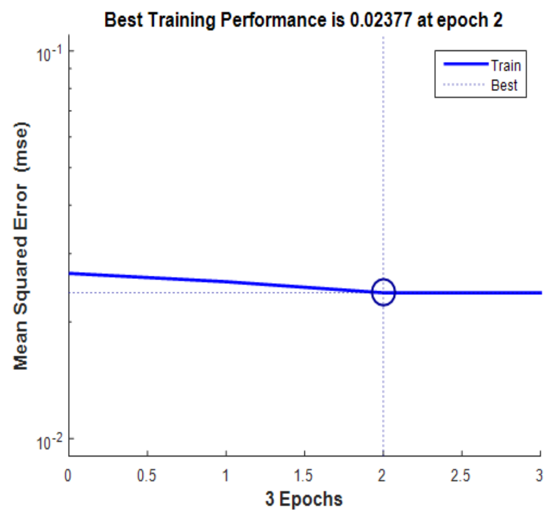

Figure 11: Training Error Analysis

From the result it was observed that the best training performance has a root mean error of 0.02377 at epoch 2. Further training evaluation was performed to justify this result in figure 12 using a regression model. The regression result is employed to monitor the fittings of the neural network performance in line with the reference plant model. This is achieved by creating a linear relationship between the output and the target. If the fitness is 100%, the linear relationship is R=1 which is the précised result for the plant. Although it is rare to achieve in practical, however if the relationship is R= < 0.5, then the performance of the neural network controller is very poor and need to be re-trained.

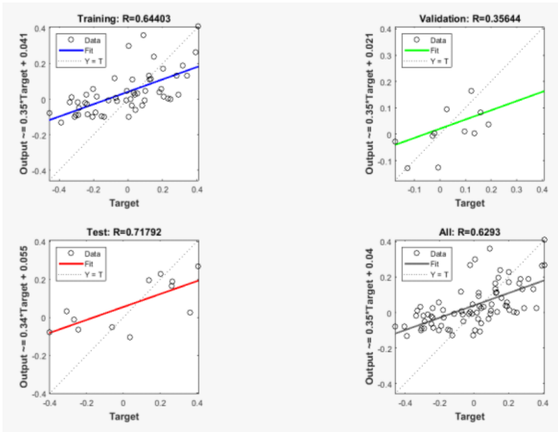

Figure 12: Regression (1)

From the result in figure 12 it was revealed that the relationship between the training, testing and validation result are not accurate (0.6293). This is not acceptable in this case and will greatly affect the performance of the neuro sensor response. To improve this result, the system was retrained and this time produced a desired validation result as shown in figure 13

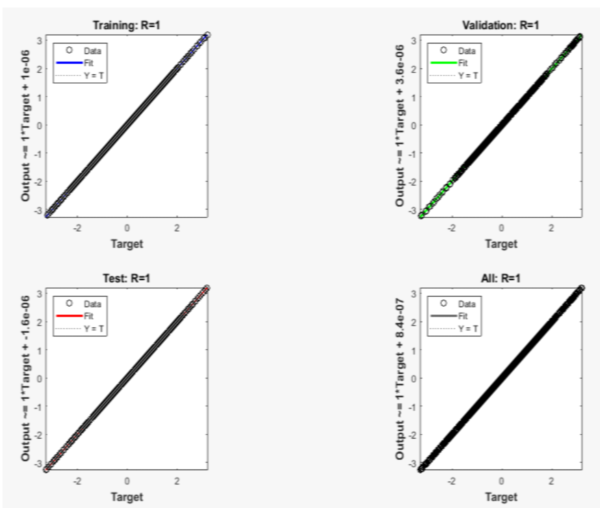

Figure 13: Regression (2)

From the result in figure 13; it was observed that the relationship between the target and the output at R= 1 was achieved. This was possible due to the series of training process performed before achieving this desired result.

4.2 Results of the NN-FL integration for flood detection and control

This section presented the performance of the system integration when the NN-FL was used to develop improved flood detection and monitoring system. The system when tested on the river during flood condition showed collected the flood parameters in the table 3;

Table 3: Performance for flood detection system with NN-FL

Time interval (sec)	Flood level (cm^3/h)	Status
5.0	96.9	Green Alert
10.0	94.8	Green Alert
15.0	90.9	Green Alert
20.0	92.9	Green Alert
25.0	94.7	Green Alert
30.0	95.7	Green Alert
35.0	98.7	Green Alert
40.0	99.9	Green Alert
45.0	100.2	Green Alert
50.0	103	Green Alert
55.0	101.4	Green Alert
60.0	100.2	Green Alert
65.0	100.7	Green Alert
70.0	104.8	Green Alert
75.0	106.3	Green Alert
80.0	120.7	Green Alert
85.0	126.8	Green Alert
90.0	187.9	Green Alert
95.0	198.9	Green Alert
100.0	198.6	Green Alert
105.0	199.7	Green Alert
110.0	240.1	Green Alert
115.0	320.3	Yellow Alert
120.0	370.7	Yellow Alert
125.0	381.1	Yellow Alert
130.0	387.4	Yellow Alert
135.0	392.9	Yellow Alert
140.0	423.3	Red Alert
145.0	482.9	Red Alert
150.0	493.1	Red Alert
155.0	493.8	Red Alert

160.0	483.8	Red Alert
165.0	472.8	Red Alert
170.0	472.9	Red Alert
175.0	482.9	Red Alert
180.0	485.9	Red Alert

The table 3 presented the performance of the NN-FL system used for flood detection and monitoring. The data collected by the system which was used to classify fault was analyzed in the figure 14;

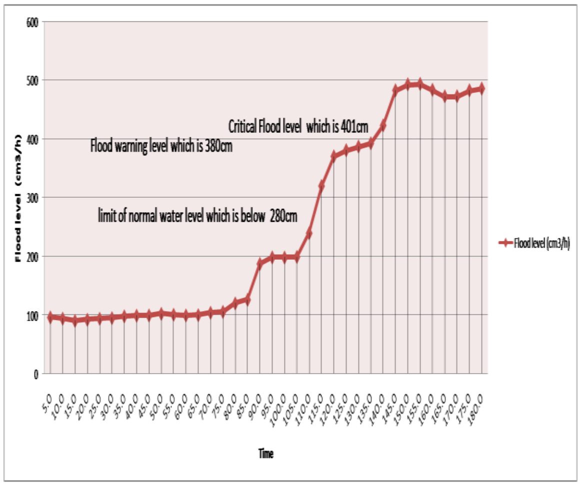

Figure 14: Result of the NN-FL system

From the result it was observed that the system classified flood when the water level rises 10cm over the 380cm which is the height for peak warning water level. The result showed how the neural network was able to read and classify flood from the reference model used in training the neurons.

4.3 Comparative analysis

The comparative analysis compared the data collected with PID-FL system against the NN-FL based system during the event of flood and the result were presented in the table 4;

Table 4: Comparative result

Time interval (sec)	**Flood level (cm^3/h) with NN-FL**	**Flood level (cm^3/h) with PID-FL**
5.0	96.9	95.8
10.0	94.8	93.8
15.0	90.9	90.9
20.0	92.9	92.5
25.0	94.7	94.5
30.0	95.7	94.9
35.0	98.7	97.8
40.0	99.9	98.6
45.0	100.2	99.7
50.0	101.3	100.8
55.0	101.4	100.9
60.0	100.2	99.92
65.0	100.7	99.98
70.0	104.8	103.5
75.0	106.3	104.8
80.0	120.7	111.8
85.0	126.8	117.5
90.0	187.9	184.6
95.0	198.9	193.5
100.0	198.6	194.9
105.0	199.7	195.4
110.0	240.1	238.6
115.0	320.3	329.0
120.0	370.7	269.1
125.0	381.1	375.3
130.0	387.4	377.4
135.0	392.9	383.9
140.0	423.3	423.3
145.0	482.9	478.9
150.0	493.1	487.1
155.0	493.8	484.8
160.0	483.8	479.8
165.0	472.8	469.8
170.0	472.9	464.3
175.0	482.9	473.1
180.0	485.9	485.7

The table 4 presented the comparative performance of the flood detection system developed with NN-FL and PID-FL characterized. The result was analyzed with graph in the figure 15;

Vol. 2, Issue 5; No. 46, May, 2023, pp. 488-498

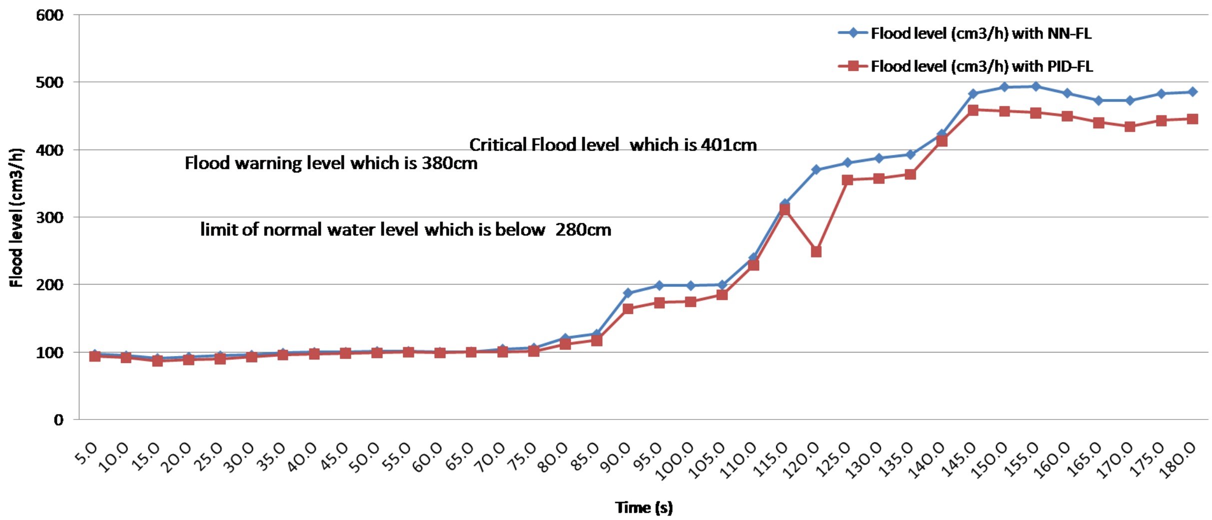

Figure 15: Comparative flood detection and monitoring performance

The figure 15 presented a comparative result of the NN-FL and PID-FL. The result showed that the NN-FL was able to sample more data when compared with the PID-FL as the flood level increases. The reason was due to the poor response time of the PID-FL which was improved with the NN-FL and in this case was able to read the flood signal aster and control. The comparative step response performance of the NN-FL and PID-FL was presented in the table 5;

Table 5: Comparative step response performance

Parameters	**PID-FL**	**NN-FL**	**Percentage improvement**
Rise time	5s	5s	0%
Settling time	41.7s	11.4s	70**(%)**
Overshoot	8.7%	0%	N/A
Dead time	46.7s	16.7s	64.2**(%)**

The table shows a comparison of two control systems for a flood classification process, where one system uses a PID and the other uses a NN. The parameters being compared are the rise time, settling time, overshoot, and dead time, and the values for each parameter are given in seconds or as a percentage improvement. The rise time of both systems is the same, indicating that both systems have similar response times in reaching their target value. The settling time of NN-FL is significantly lower than PID-FL, indicating that the NN-FL system is faster in stabilizing the process after a disturbance. The overshoot of PID-FL is 8.7%, while NN-FL has no overshoot. This means that NN-FL produces a more accurate response without overshooting the target value. The dead time of NN-FL is also significantly lower than PID-FL, indicating that the NN-FL system responds faster to changes in the process. Overall, the NN-FL system shows a significant improvement in performance compared to the PID-FL system, with a percentage improvement of 70% for settling time and 64.2% or dead time.

5. CONCLUSION

The proposed real time flood detection and monitoring system has been successfully modelled and simulate using Simulink toolbox. The requirement specification was to develop a nonlinear system that is intelligent in such a way that it can readjust its parameters and produce an output based on reference input. It is required that the system should not be complex structurally, response time should be at real time and lastly the system implementation and maintenance cost should be relatively low when compared to existing systems. It was observed from the work carried out that the requirement specifications were met. A nonlinear neuro model predictive control system which utilizes previous process control behaviour to foretell future response of the system was modelled and implemented in Simulink. The developed mathematical models were transformed into discrete form using Laplace transform to establish the transfer functions for development of the Simulink model for real time simulation. Simulation results of the system shows that the proposed system achieved a regression result of R=1 after various iteration during training. The significance of this result is that the monitoring of changes in the parameters of the sensor which is time dependent can be done in real time. From the result also, it was observed that the proposed system responded very fast to flood signal within 11.4 seconds as against 41.7seconds achieved from the work of Amy, (2016). The proposed system was validated to determine improvement by comparing the response times achieved by the two systems. It was found that the proposed system achieved a 64.2% improvement when compared with the conventional PID system.

6. REFERENCES

Abdirahman O., Abdullahi A., Mohamed A., Siti Z., Octavio E., (2021). "A Real-Time Flood Detection System Based on Machine Learning Algorithms with Emphasis on Deep Learning",International Journal of Engineering Trends and Technology Volume 69 Issue 5, 249-256,ISSN:2231–5381/doi:10.14445/22315381/IJETT-V69I5P232

Elizabeth A., Sai R.,&Daniela R., (2008). "Model-Based Monitoring for Early Warning Flood Detection",SenSys'08, November 5–7, 2008, Raleigh, North Carolina, USA. Copyright 2008 ACM 978-1-59593-990-6/08/11

Gadade M., Patil B., Salgar M., Dabhole A., (2019). "Early Flood Detection System using Android Application",International Journal of Engineering Research & Technology (IJERT) http://www.ijert.org ISSN: 2278-0181 IJERTV8IS070260 Published by: www.ijert.org

Joe M.,& Alexander H., (2019)."Developing a Flood Risk Assessment Using Support Vector Machine And Convolutional Neural Network: A Conceptual Framework", in March 9, 2019, 15 th International Colloquium on signal processing and Applications

Mousa M., Zhang X.,&Claudel C., (2016). "Flash Flood Detection in Urban Cities Using Ultrasonic and Infrared Sensors",Institute of Electrical and Electronics Engineers (IEEE). 10.1109/JSEN.2016.2592359.

Murmu I., and Yadav L. (2013) "Low-Cost Automatic Water Level Control for Domestic Applications, Q.C: Automatic Monitoring"; IJRSC; vol 4 (2); pp. 90-101.

Nalini R., Nathiya M., Vikas K., Surya S., Raghu R., Rahul S., (2020). "Automatic Flood Detection and Monitoring System",Studia Rosenthaliana (Journal for the Study of Research) Volume XII, Issue V, May-2020 ISSN NO: 1781-7838

Okafor P., Eneh I.,&Eneh P., (2017). "Improving the Control of Dc Servomotor Speed and Position Using Model Reference Adaptive Control (MRAC)". International Journal of Research in Engineering and Applied Sciences (IJREAS) Vol. 7 Issue 8, ISSN (O): 2249-3905, pp. 103-119.

Sandhya K.,Shejina (2021). "Flood Forecasting:An Intelligent System Using Machine Learning",Vol-7 Issue-3 2021 IJARIIE-ISSN(O)-2395-4396

Tibin M., PrabhakaranN., (2017). "Real time WSN based flood detection and control monitoring system", International Conference on Intelligent Computing, Instrumentation and Control Technologies.

Toni B., Patrick W., Po-Kuan C., Niel H., Jean B., and Bart M. (2010) "Flood regulation using nonlinear model predictive control." Control engineering practices 18 (2010) ISSN: 1147-1157; pp. 128-135.