Fault Detection and Diagnosis of various Mechanical Components in a Nuclear Power Plant combining Noise Analysis and Machine Learning Techniques

Ankit Ghosh[1], Purbita Kole[2], Alok Kole[3]

[1]PG Student, School of Nuclear Studies and Application, Jadavpur University, Kolkata, India
[2]UG Student, Department of Physics, Christ University, Bangalore, India
[3]Professor, Department of Electrical Engineering, RCC Institute of Information Technology, Kolkata, India

---***---

Abstract - *There are several types of mechanical components in a Nuclear Power Plant (NPP) varying in design and applications. Faults occurring in these machines may cause disastrous accidents, disruption of power supply, economic loss, environmental pollution and even loss of life. Effective diagnosis of these faults is important to prevent major accidents and to protect the mankind from undue radiation hazards. This research presents the development of an efficient model for the early detection of failures in various mechanical components in a NPP combining noise analysis and machine learning algorithms. The proposed technique formulates a fault detection and classification problem as an Artificial Neural Network (ANN). The acoustic spectrum of a pump operating in a NPP has been considered. Several test cases have been taken into account for the generation of training data and test data for the proposed ANN model. The model has been then trained using the Mini-Batch Stochastic Gradient Descent optimization algorithm and a performance evaluation of the model has been done to ensure its reliability. The test results obtained have been satisfactory and it can be inferred that the proposed model is capable of identifying the fault cases accurately.*

Key Words: **acoustic spectrum, artificial neural network, fault detection and classification, machine learning, mechanical components, noise analysis**

1. INTRODUCTION

For fault detection and diagnosis in rotating machines, vibrational analysis is used [1]. It is possible to determine the nature and severity of the fault by measuring and analysing the vibration of a machine. A method that is employed for studying mechanical vibration is spectral analysis. The vibrational signals carry information regarding the mechanical elements. These signals usually are a combination of the fundamental frequency with a narrowband frequency component and the harmonics. The development of Fast Fourier Transform (FFT) has eased the task. The measured time-domain vibrational signals are converted into frequency domain values using FFT [2]. The FFT approach is very useful in estimating the spectral information [3]. By analysing the FFT spectrum it is possible to identify that a fault may have occurred. Sporadic peaks occur in the spectrum during the fault condition as compared to the normal operating conditions. By studying the two spectrums, the fault condition can be determined. For instance, a pump in perfect working condition will adhere to a signature vibration spectrum. Now, if the pump starts to develop a certain fault, like a loose screw or a bearing failure its vibration spectrum will change. By studying the two vibration spectrums the healthy working condition of the pump can be differentiated from the faulty condition. A nuclear power plant consists of different types of pumps. Sound of a pump changes due to a fault. An expert can detect the change in noise. However; such an approach is prone to human error. Physically checking the faults in various mechanical components will be time consuming and there is a chance of even missing out on a few components. In this context the use of machine learning (ML) tools becomes much more obvious and logical to deal with challenges of fault diagnosis. If ML approach is employed it will give an indication to the service personnel that something might have gone wrong. A ML approach for fault detection and classification of machines is an efficient way to release the contribution from human labour and automatically determine the health states of machines [4]. Deep Learning is a subset of ML which in turn is a subset of Artificial Intelligence (AI). Deep Learning is a type of ML inspired by the structure of the human brain. In terms of deep learning this structure is called an Artificial Neural Network (ANN). ANN is a computing system which is designed to simulate in the same way as the human brain analyses and processes information [5]. ANNs have self-learning capabilities. They produce better results as more data is made available. ANNs take in data, train themselves to recognize the patterns in this data and then predict the outputs for a new set of similar data [6]. For fault detection and classification, ANNs are applied [7] [8] [9] [10].

2. DATASETS

Keeping in mind the acoustic spectrum of a pump, the following test cases have been considered:
1. Only Noise (N (0, 1)) is present
2. Noise (N (0, 1)) along with 1 KHz frequency peak is present

3. Noise (N (0, 1)) along with 10 KHz frequency peak is present
4. Noise (N (0, 1)) along with 20 KHz frequency peak is present
5. Noise (N (0, 1)) along with 1 KHz and 10 KHz frequency peaks is present
6. Noise (N (0, 1)) along with 1 KHz and 20 KHz frequency peaks is present
7. Noise (N (0, 1)) along with 10 KHz and 20 KHz frequency peaks is present
8. Noise (N (0, 1)) along with 1 KHz, 10 KHz and 20 KHz frequency peaks is present.

Gaussian Noise (N (0, 1)) has been considered because it emulates the effect of any random process that occurs in nature.

The study of fluctuating noise involves FFT. Hence, 512 point FFT of the individual signals has been computed using python programming language.

The information within the frequency spectrum is entirely symmetric. The negative frequencies being redundant they have been ignored. Only the positive frequencies have been considered and they have been saved for further processing. 80,000 training data and 10,000 test cases have been generated.

Fig-1 shows the signal corresponding to case 1. Fig-2, 3, 4, 5, 6, 7, 8 show the FFT plots of the signals corresponding to cases 2,3,4,5,6,7,8 respectively.

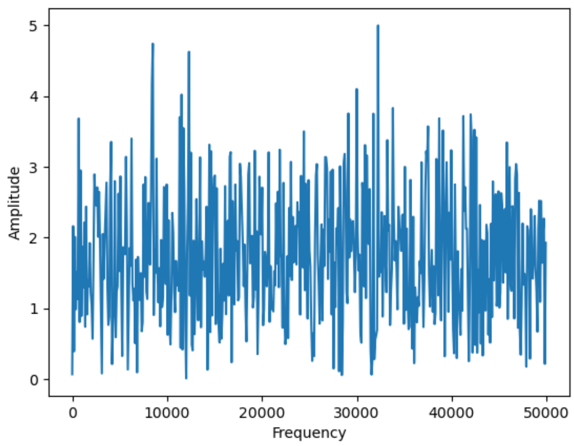

Fig-1: Plot showing the signal containing only noise

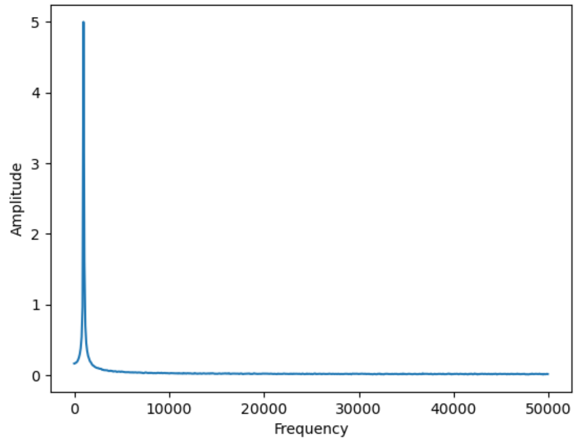

Fig-2: Plot showing the FFT of the signal containing noise and 1 KHz frequency peak

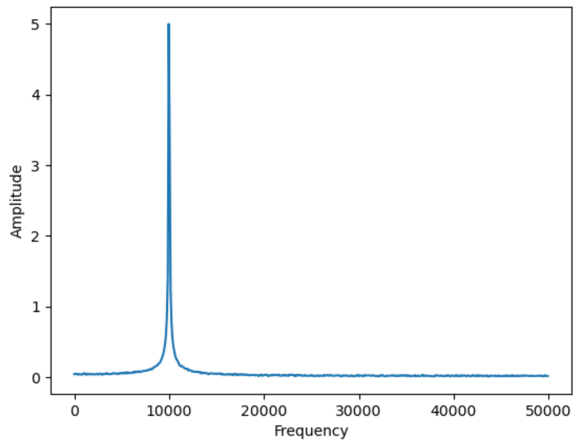

Fig-3: Plot showing the FFT of the signal containing noise and 10 KHz frequency peak

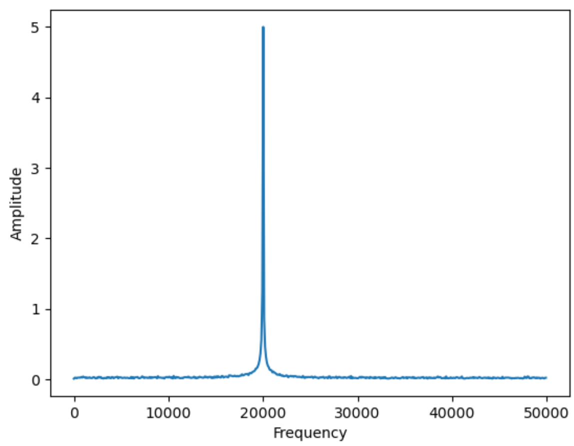

Fig-4: Plot showing FFT of the signal containing noise and 20 KHz frequency peak

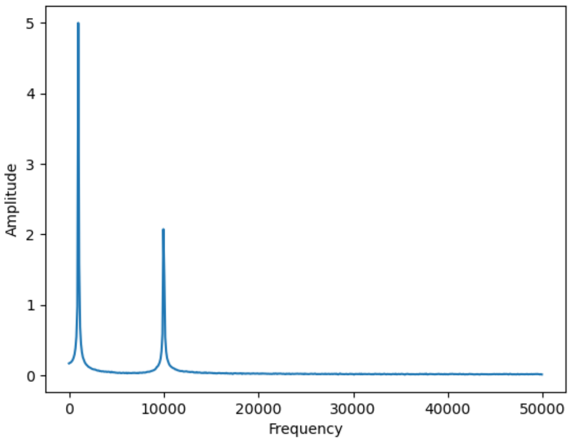

Fig-5: Plot showing FFT of the signal containing noise and 1 KHz and 10 KHz frequency peaks

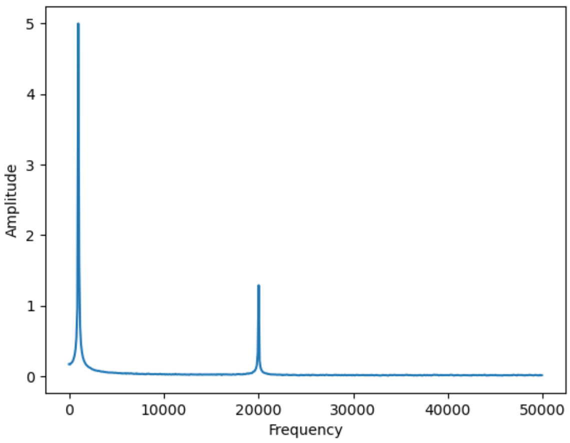

Fig-6: Plot showing FFT of the signal containing noise and 1 KHz and 20 KHz frequency peaks

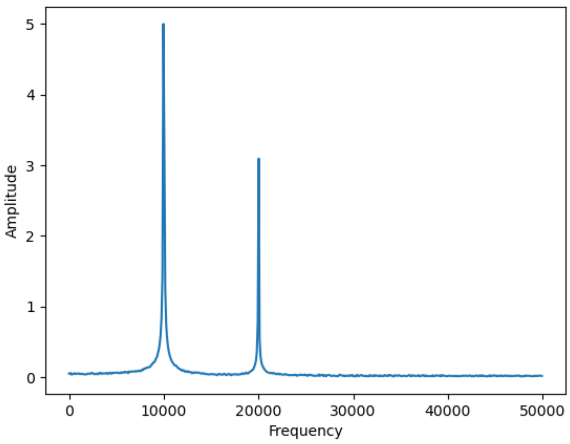

Fig-7: Plot showing FFT of the signal containing noise and 10 KHz and 20 KHz frequency peaks

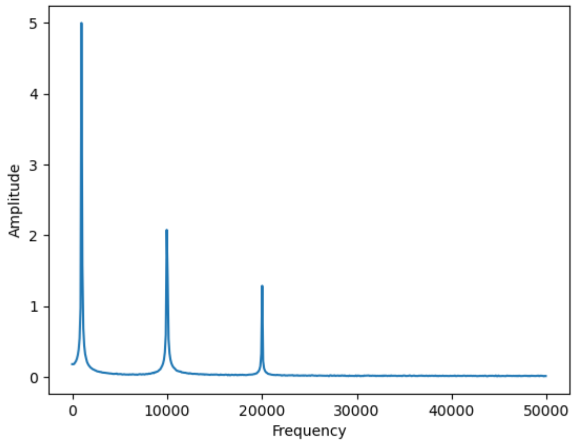

Fig-8: Plot showing FFT of the signal containing noise along with 1 KHz, 10 KHz and 20 KHz frequency peaks

3. METHODOLOGY

The proposed work flow has been illustrated in Fig-9.

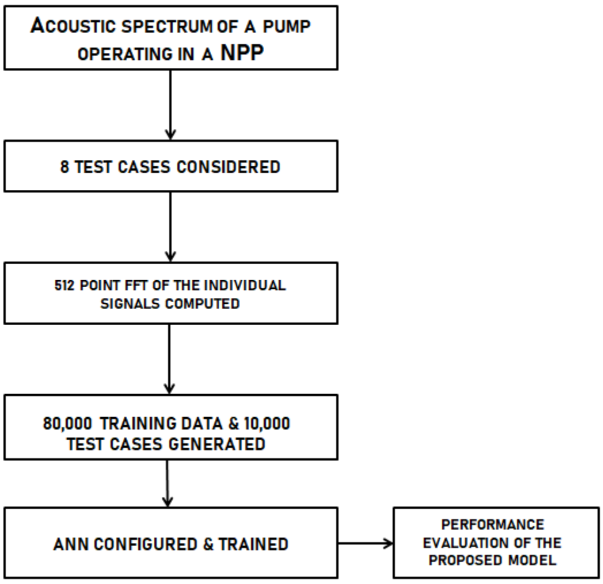

Fig-9: Proposed work flow

3.1 Proposed Artificial Neural Network Architecture

An ANN has been modeled with an input layer having 512 nodes, one hidden layer with 15 nodes and an output layer with 8 nodes. 512 point FFT of the individual signals have been computed. So, at the input layer 512 nodes have been considered. The 8 output nodes correspond to the 8 cases that need to be classified. 15 nodes at the hidden layer have been chosen based on the performance of the ANN with different number of hidden layer nodes.

The architecture of the ANN that has been configured has been shown in Fig-10.

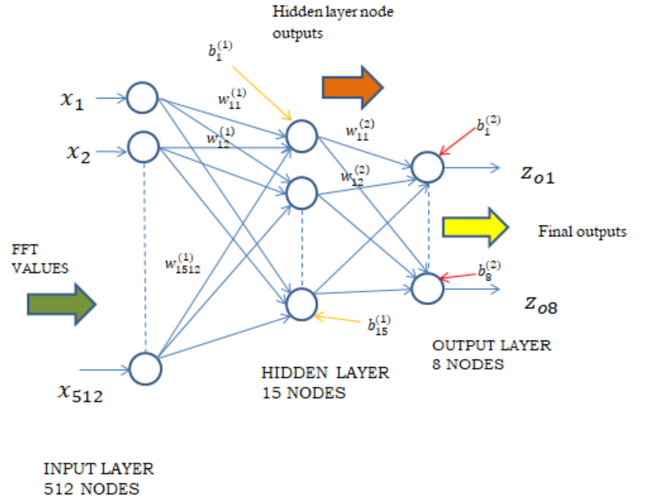

Fig-10: Proposed Artificial Neural Network Architecture

3.2 Optimization algorithm

Mini-Batch Stochastic Gradient Descent has been used as the optimization algorithm. It takes a small sample of data points instead of a single data point during each iteration. This sample of data points is called the mini-batch and hence the name of the optimization algorithm.

3.3 Loss function

In this work Mean Squared Error has been used as the loss function. By taking the mean of the squared differences between the actual or the target values and the predicted values, the loss is calculated.

3.4 Activation function

In this work both sigmoid and Rectified Linear Unit (ReLU) have been used as activation functions. Sigmoid is a function and it is plotted as 'S' shaped graph as depicted in Fig-11. Equation: f(x) = 1/ (1+ e^-x)

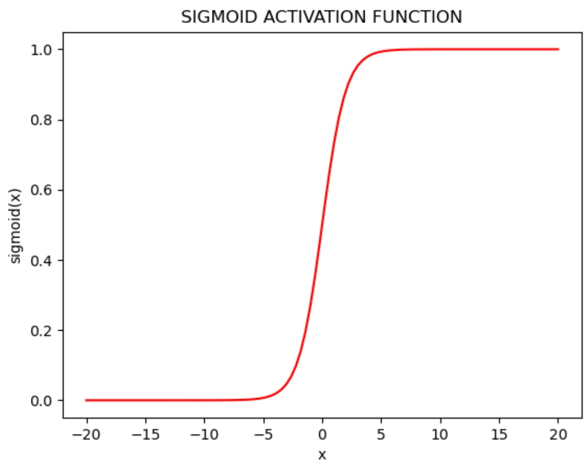

Fig-11: Plot showing the sigmoid activation function

ReLU is a commonly used activation function. Equation: R (x) = max (0, x)

R(x) =0, when x<0

x , when x>0, ReLU is half rectified (from the bottom)

The range of the function is between 0 and infinity. The plot of ReLU activation function has been shown in Fig-12.

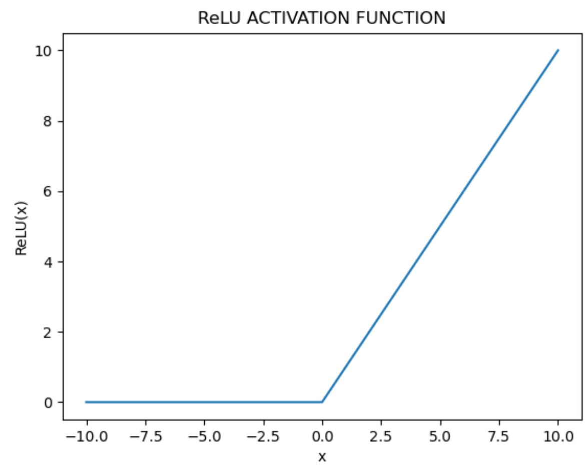

Fig-12: Plot showing the ReLU activation function

The entire code for the proposed ANN model has been implemented using python.

4. RESULTS AND DISCUSSION

The python code has been executed twice.

1. by using sigmoid activation function at the nodes of the hidden layer as well as at the nodes of the output layer

2. by using sigmoid activation function at the nodes of the hidden layer and ReLU at the nodes of the output layer

The following parameters have been modified to obtain the values of minimum error for comparison.

- Learning Rate (eta)
- Regularization Parameter (el)
- The Mini-batch Size (mini-batch)
- The seed for initialization of weights and biases (init_seed)

The test results that have been obtained using sigmoid activation function at the nodes of the hidden layer as well as at the nodes of the output layer have been shown in Table-1. The minimum error that has been obtained is 0.60% for eta = 0.003, el = 20, mini-batch = 20 and init_seed = 20,000.

Table-1: Test Results with sigmoid at hidden and output layer nodes

eta	el	mini-batch	init_seed	epoch	Minimum error
0.005	20.0	20	20,000	7	0.63%
0.004	20.0	20	20,000	8	0.66%
0.003	**20.0**	**20**	**20,000**	**11**	**0.60%**
0.002	20.0	20	20,000	16	0.64%
0.001	20.0	20	20,000	26	0.63%
0.10	20.0	20	20,000	1	0.69%
0.20	20.0	20	20,000	10	0.74%

Fig-13 shows the percentage error vs. epoch plot obtained on training the ANN model with python using sigmoid activation function at the nodes of the hidden layer as well as at the nodes of the output layer with the following parameter values: eta = 0.003, el = 20, mini-batch = 20 and init_seed = 20,000.

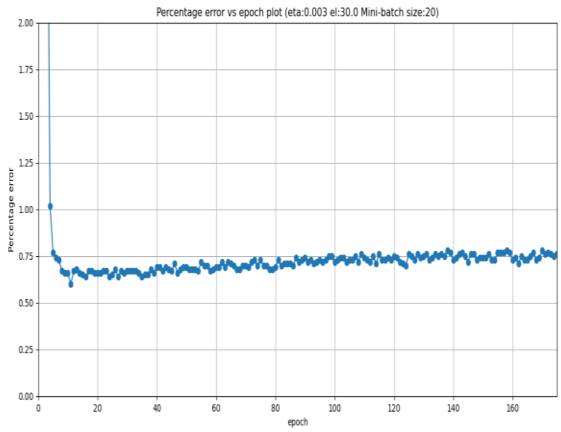

Fig-13: Plot showing percentage error vs. epoch using sigmoid activation function at the hidden and output layer nodes

The test results that have been obtained using sigmoid as an activation function at the nodes of the hidden layer and ReLU activation function at the nodes of the output layer have been shown in Table 2. The minimum error that has been obtained is 0.61% for eta = 0.005, el = 30, mini-batch = 10 and init_seed = 20,000.

Table-2: Test Results with sigmoid at the hidden layer and ReLU at the output layer

eta	el	mini-batch	init_seed	epoch	Minimum error
0.005	**30.0**	**10.0**	**20,000**	**12**	**0.61%**
0.004	30.0	10.0	20,000	15	0.63%
0.003	30.0	10.0	20,000	4	0.63%
0.002	30.0	10.0	20,000	13	0.62%
0.001	30.0	10.0	20,000	19	0.63%
0.10	30.0	10.0	20,000	27	7.51%
0.20	30.0	10.0	20,000	35	10.08%

Fig-14 shows the percentage error vs. epoch plot that has been obtained using sigmoid activation function at the hidden layer nodes while ReLU at the output layer nodes with the following parameter values: eta = 0.005, el = 30, mini-batch = 10 and init_seed = 20,000.

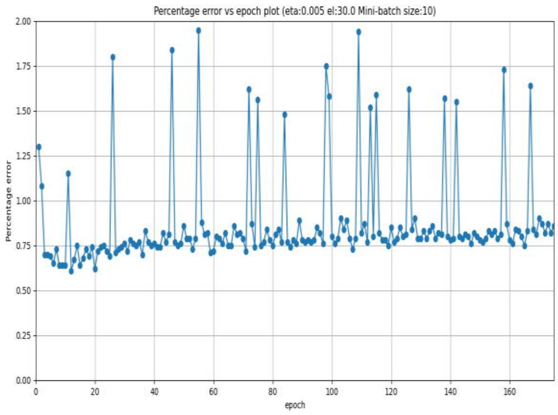

Fig-14: Plot showing percentage error vs. epoch using sigmoid at the hidden layer nodes and ReLU at the output layer

4.1 Performance comparative analysis of the proposed model

The choice of a suitable activation function in the hidden layer nodes enhances the learning capability of the ANN while choosing a proper activation function at the output layer nodes helps the ANN make better predictions. A comparative analysis of the performance of the proposed ANN model using different activation functions has been done and the test results obtained have been discussed in Table-3.

Table-3: Performance analysis of the ANN model using different activation functions

Activation function at the hidden layer nodes	Activation function at the output layer nodes	Minimum percentage error
sigmoid	sigmoid	0.60
sigmoid	ReLU	0.61

From the test results obtained it can be concluded that the performance of the ANN model under both the cases has been satisfactory.

5. CONCLUSION

Early detection of faults in various mechanical components such as industrial pumps is essential because of the following factors, increased reliability and reduction of energy consumption, service and maintenance costs. But, the most important factor is safety. Early detection of failure can help avoid abnormal events. This paper presents a detailed overview of how an efficient fault detection and diagnosis model can be developed combining the two techniques, noise analysis and machine learning algorithms. The fault detection and classification problem has been formulated as an artificial neural network. The vibrational spectrum of a pump working in a nuclear power plant has been considered in both normal and faulty operating conditions. Training data and test data have been generated to train the model. From the test results obtained it can be concluded that the proposed model has been able to identify the fault conditions. The scope of this paper is not restricted to a nuclear power plant; the proposed methodology can be used to predict faults before they happen in any power plant and industries involving machinery. The proposed model can be implemented on hardware using Field Programmable Gate Array.

REFERENCES

[1] Saeid Farokhzad, "Vibration Based Fault Detection of Centrifugal Pump by Fast Fourier Transform and Adaptive Neuro-Fuzzy Inference System", Journal of Mechanical Engineering and Technology, Vol. 1 Issue. 3, December 2013.

[2] Cihun-Siyong Alex Gong,Huang-Chang Lee, Yu-Chieh Chuang, Tien-Hua Li, Chih-Hui Simon Su, Lung-Hsien Huang, Chih-Wei Hsu, Yih-Shiou Hwang, Jiann-Der Lee, and Chih-Hsiung Chang, " Design and Implementation of Acoustic Sensing System for Online Early Fault Detection in Industrial Fans", Hindawi Journal of Sensors, Vol. 2018, June 2018.

[3] Geoffrey C. Scott, Daniel K. Bogen, Edward Korostoff, "FFT Performance in the Presence of Noise", IEEE Transactions on Biomedical Engineering, Volume: BME-34, Issue 6, June 1987.

[4] Ndeye Lo, Jean-Marie Flaus, Olivier Adrot, "Review of Machine Learning Approaches In Fault Diagnosis applied to IoT System", International Conference on Control, Automation and Diagnosis ICCAD'19, July 2019, Grenoble, France

[5] Manish Mishra, Monika Srivastava, "A view of Artificial Neural Network", 2014 International Conference on Advances in Engineering and Technology Research (ICAETR-2014), 1-2 Aug. 2014, Unnao, India.

[6] Jiahao Lu, Xianghua Luo, Dongsheng Liu, Peng Liu, Bo Liu, "A Configurable Architecture of ANN in Hardware with Resource-Efficient Reusable Neuron", 2019 IEEE 13th International Conference on ASIC (ASICON), 29 Oct. – 1Nov. 2019, Chongqing, China.

[7] Richard Grisel,Thierry Dumartin,Giansalvo Cirrincione, "VHDL implementation of a neural diagnosis system: application to induction machine fault detection",2004 IEEE International Symposium on Industrial Electronics, 4-7 May 2004, Ajaccio, France.

[8] A. K. Onaolapo, K. T. Akindeji, "Application of Artificial Neural Network for Fault Recognition and Classification in Distribution Network", 2019 South

African Universities Power Engineering Conference/Robotics and Mechatronics/Pattern Recognition Association of South Africa (SAUPEC/RobMech/PRASA), 28-30 Jan. 2019, Bloemfontein, South Africa.

[9] Asma Khelifi, Nadhir Mansour Ben Lakhal, Hajer Gharsallaoui, Othman Nasri, "Artificial Neural Network-based Fault Detection", 2018 5th International Conference on Control, Decision and Information Technologies (CoDIT), 10-13 April 2018, Thessaloniki, Greece.

[10] Alok Kole, "Design and Stability Analysis of Adaptive Fuzzy Feedback Controller for Nonlinear Systems by Takagi-Sugeno Model based Adaptation Scheme", International Journal of Soft Computing, Vol.19,Issue 6,2015,Page:1747-1763, Springer SCI Indexed.