A novel approach of fault detection using artificial neural network (ANN)

Ms. S. S. Patil
Dept. of Computer Engineering
Smt. Kashibai Navale College of Engineering
Vadgaon(Bk), Pune
(Affilated to the Savitribai Phule Pune University)

Prof. S. K. Pathan
Dept. of Computer Engineering
Smt. Kashibai Navale College of Engineering
Vadgaon(Bk), Pune
(Affilated to the Savitribai Phule Pune University)

***Abstract*—It is very much required to detect and diagnose fault of machine in process industry. It will help to maintenance of machine. There are many output parameters which directly affects due to fault. It can be any form like waves, numerical values etc. It is possible to achieve this by artificial intelligence methods. The methods like artificial neural network (ANN), fuzzy logic or may be hybrid model which includes combination of two or more methods. The Neuro-fuzzy system (NFS), after training with machine condition data, is employed as a prognostic model to forecast the evolution of the machine fault state with time. NFS residuals between the actual and predicted condition data. Statistical methods with ANN or fuzzy is also possible to use to detect and diagnose fault. In this Artificial neural network (ANN) have used to detect fault. Continuously analyzing the data produces by machine it may be form of table, graph or any other form. The defect or fault of machine must be affects on result it produces so by reading or by identifying some parameters it is possible to detect fault. Multilayer backpropagation algorithm of ANN will travels the input through different layers and produces output if error is there then back propagate and change weights accordingly. ANN provide behavior of different parameters by continuously analyzing the result of machine and determine there is any effect on components of machine by using parameter values.**

Keywords—Artificial neural network, backpropagation algorithm, multilayer network.

I. INTRODUCTION

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain,

process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANNs as well.

An artificial neuron is a device with many inputs and one output. The neuron has two modes of operation; the training mode and the using mode. In the training mode, the neuron can be trained to fire (or not), for particular input patterns. In the using mode, when a taught input pattern is detected at the input, its associated output becomes the current output. If the input pattern does not belong in the taught list of input patterns, the firing rule is used to determine whether to fire or not.

The firing rule is an important concept in neural networks and accounts for their high flexibility. A firing rule determines how one calculates whether a neuron should fire for any input pattern. It relates to all the input patterns, not only the ones on which the node was trained.

Fault detection and diagnosis is important and difficult topics in the engineering field. With proper machine monitoring and fault detection schemes, improved safety and reliability can be achieved for different engineering system operations. The importance of incipient fault detection can be found in the cost savings which are realized by detecting potential machine failures before they occur. Non-invasive, inexpensive, and reliable fault detection techniques are often referred by many engineers. Many of the inexpensive and noninvasive techniques available for fault detection and diagnosis in machines are based on mathematical models of the system of interest, such as parameter estimation (model based techniques). However, since most machine dynamics are non-linear and stochastic, many assumptions must be made regarding the system in order to arrive at a simple and reasonable mathematical model of the machine. In other words, the fault detection or diagnosis system is not robust enough in the presence of noise and perturbations because the underlying mathematical model of the system is not well represented. The emerging artificial neural network technology has been applied successfully to perform monitoring and fault detection of different engineering systems, such as motors and power distribution systems. The demand for the use of artificial neural networks to solve engineering problems is expected to increase significantly in the next ten years, due to several breakthroughs in this field and also to the limitations of the conventional engineering problem solving techniques. Artificial neural network configurations, training data requirements, robustness issues, and design considerations of motor fault detection have been investigated. Results to date have demonstrated their significant performance advantages relative to the conventional methods. Although the ANN can provide the correct input-output fault detection relation, it is essentially a

ISSN: 2278 – 1323

"black box" device; i.e., it does not provide heuristic reasoning about the fault detection process.

II. MOTIVATION

Nowadays it's very important and efficient for productivity of machine and ultimately industry performance and productivity. In traditional fault management need to repair after breakdown if user have extra component in spare even though it will take time to change and for that moment work or production stops and it happens when it is automatically running on field without any supervisor for some time then it was costs a lot.

To take decision well in advance is not present in existing system. In existing system fault is known only if it occurs and then need to take appropriate action on that there is no any provision to predict fault. In existing system there is neither artificial neural network implemented nor fuzzy logic to take intelligence decision regarding fault detection well in advance. If it predict before someday then will get the time to think and took appropriate decision it will increase efficiency.

III. RELATED WORK

Abu-Rub, H. and Saad, M.S proposes an effective approach to detect, isolate, and identify fault severity and post fault operation of permanent magnet synchronous motors (PMSM) in the presence of stator winding turn fault. The paper proposes fault tolerant operation of PMSM under post condition with stator winding turn fault by using grounded neutral point through controllable impedance using artificial neural network (ANN). The fault detection and diagnosis is achieved by using a strategy based on the analysis of the ratio of third harmonic to fundamental waveform obtained from Fast Fourier Transform (FFT) of magnitude components of the stator currents. The strategy helps to detect stator turn fault, isolate the faulty components, and estimate different insulation failure percentages and remedial operation of PMSM in the presence of stator winding turn fault. The model of PMSM with stator winding turn fault is simulated at different load conditions using a (2-D) Finite Element Analysis (FEA). Experimental results demonstrate the validity of the proposed technique [1].

Ahmed, R. and Ryan Ahmed propose an engine fault detection and classification technique using vibration data in the crank angle domain is presented. This data is used in conjunction with artificial neural networks (ANNs) as applied to detect faults in a four-stroke gasoline engine built for experimentation. A comparative study is provided between the popular back propagation (BP) method, the Levenberg-Marquardt method, the Quasi-Newton method, the extended Kalman filter (EKF), and the smooth variable structure filter (SVSF). The SVSF is a relatively new estimation strategy, based on the sliding mode concept. It has been formulated to efficiently train ANNs, and is consequently referred to as the SVSF-based ANN. The accuracy of the proposed method is compared with the standard accuracy of the Kalman-based filters and the popular back propagation algorithms, in an effort to validate the SVSF-ANN performance and application to engine fault detection and classification. The customizable fault diagnostic system is able to detect known engine faults with various degrees of severity, such as: defective lash adjuster, piston chirp, and chain tensioner problems. The technique can be used at any dealership or assembly plant to considerably reduce warranty costs for the company and manufacturer [2].

Schmitt, H.L. proposes Fault detection in electrical machines has been widely explored by researchers, especially bearing faults that represent about 40% to 60% of the total faults. Since this kind of fault is detectable by particular frequencies at the stator current, it is now a source of investigation. Thus, this work presents a predictability analysis method based on relative entropy measures estimated over reconstructed signals obtained from wavelet-packet decomposition components. The signals were simulated using a real motor current signal with addition of frequency components related to the bearing faults. Using three ANN topologies, these entropy measures are classified in two groups: normal and faulty signals with a high performance rate [3].

Refaat, S.S proposes Permanent magnet synchronous motor (PMSM) is currently the most attractive application electric machine for several industrial applications. It has obtained widespread application in motor drives in recent time. However, different types of faults are unavoidable in such motors. This paper focuses on stator winding faults diagnosis. This paper proposes the ratio of third harmonic to fundamental FFT magnitude component of the three-phase stator line current and supply voltage as a parameter for detecting stator winding turn faults under different load conditions and using artificial neural network (ANN). Discrimination among unbalancing of supply voltage conditions and stator turn short circuit poses a challenge that is addressed in this paper. The presented approach yields a high degree of accuracy in fault detection and diagnosis between the effects of stator winding turn fault and those due to unbalanced supply voltages using artificial neural network. All simulations in this paper are conducted using finite element analysis software [4].

Khireddine, M.S. propose A fault, if undetected, could have catastrophic consequences (in systems such as aircraft, robotic systems and nuclear reactors) and could incur financial losses (such as in a production process). In this paper the artificial neural networks are used for both residual generation and residual analysis. A Multilayer Perceptron (MLP) is employed to reproduce the dynamics of the robotic manipulator. Its outputs are compared with actual position and velocity measurements, generating the so-called residual vector. The residuals, when properly analyzed, provide an indication of the status of the robot (normal or faulty operation). The ANN architecture employed in the residual analysis is also a multilayer perceptron (MLP) or a radial basis function network (RBFN) which uses the residuals of position and velocity to perform fault identification. Simulations employing a SCARA robotic manipulator are showed demonstrating that the system

ISSN: 2278 – 1323

can detect and isolate correctly faults that can occur during the performance of its task. We opted in our study on fault diagnosis for a dual neural classification. Thus, the architecture of the proposed approach is based on two types of classifiers: Firstly a classifier consisting only of one neural network (MLP or RBF) followed by a comparison of the results of detection and localization. Secondly a classifier consisting of two neural networks (RBF and MLP) and is followed by a final decision system [5].

Weilin Li proposes a fault detection and classification method for medium voltage DC (MVDC) shipboard power systems (SPSs) by integrating wavelet transform (WT) multire solution analysis (MRA) technique with artificial neural networks (ANNs). The MVDC system under consideration for future all-electric ships presents a range of new challenges, in particular the fault detection and classification issues addressed in this paper. The WT-MRA and Parseval's theorem are employed in this paper to extract the features of different faults. The energy variation of the fault signals at different resolution levels are chosen as the feature vectors. As a result of analysis and comparisons, the Daubechies 10 (db10) wavelet and scale 9 are the chosen wavelet function and decomposition level. Then, ANN is adopted to automatically classify the fault types according to the extracted features. Different fault types, such as short circuit faults on both dc bus and ac side, as well as ground fault, are analyzed and tested to verify the effectiveness of the proposed method. These faults are simulated in real time with a digital simulator and the data are then initially analyzed with MATLAB. The case study is a notional MVDC SPS model, and promising classification accuracy can be obtained according to simulation results. Finally, the proposed fault detection algorithm is implemented and tested on a real-time platform, which enables it for future practical use [6].

Moosavi, S.S proposes Traction Motors Condition Monitoring is one of the important factors in increasing motor life time and prevention of any train sudden stop in track and thereupon avoiding interruptions in track traffic. In this paper, a neural network based method for detecting unbalanced voltage fault which is one of the various faults in 3-phase traction motors was surveyed. Proposed method is independent from load state and fault percentage; which means neural network is able to detect fault and load condition without any assumption about the state of the load and fault. In proposed method, two separate neural networks are used for each problem. Experimental acquired data is used to train neural networks. Based on first test results, the neural structure could detect unbalanced voltage fault percentage with 98.5% precision. Also, based on second test results, the neural network could detect load condition accurately in 97% of the cases. According to these results, neural network is a good choice for solving similar problems [7].

Iyer, K.L.V. proposes Too much dependence on large, polluting and expensive generation is no longer an option that Canadians would endorse in this era of distributed generation through renewable energy systems. Understanding the significance and prospects of self-excited induction generators (SEIGs) in distributed wind power generation, this paper presents an exclusive study of fault and a artificial neural network (ANN) based technique for its detection across the stator terminals of the SEIG. Firstly, two-axis model of a 7.5 hp industrial copper-rotor SEIG is developed to perform numerical investigations under static loading conditions, faulty conditions and hence derive data for designing the ANN based detection scheme. Fault tolerant capability of the machine is experimentally elicited by applying a short-circuit fault across the terminals of the machine and the need for fault detection in the SEIG system is discussed. Lastly, a novel ANN based scheme is developed for fault detection and numerical investigations are performed to illustrate the performance of the developed scheme. This paper aims to provide a good study to understand and develop a ANN based device for fault detection in a SEIG system [8].

Altaf, S proposes Signature analysis methods have been proven to deliver good results in the laboratory environment and successfully applied to isolated motors. The influence of fault signal on a non-faulty motor may be interpreted as faulty condition of the healthy motor. Therefore, it is difficult to identify a motor fault within a network and precisely identify the type of fault. This paper presents a supervised distributed Artificial Neural Network (ANN) that is able to identify multiple fault types such as broken rotor bar (BRB) or air gap eccentricity faults as well as the location of fault event within an industrial motor networks. Features are extracted from the current signal, based on different frequency components and associated amplitude values with each fault type. A set of significant fault features such as synchronized speed, rotor slip, the amplitude value of each fault frequency components, the Root Mean Square (RMS) and Crest Factor (CF) value are used to train the ANN using Back Propagation (BP) algorithm. The simulation results show that the proposed technique is able to identify the type and location of fault events within a distributed motor network. The proposed architecture works well with the selection of a significant feature sets and accurate fault detection result has been achieved. Classification performance was satisfactory for healthy and faulty conditions including fault type identification [9].

Refaat, Shady S proposes the possibility of developing incipient fault diagnosis and remedial operating strategies, which enable a fault tolerant induction motor star-connected winding with neutral point earthed through a controllable impedance using artificial neural network (ANN). The fault detection and diagnosis is achieved by using a strategy that detects stator turn fault, isolates the faulty components, identifies fault severity and reduces the propagation speed of the incipient stator winding fault. The fault tolerance is obtained by controlled neutral grounding resistor. This allows for continuous free operation of the induction motor even with stator winding faults. The advantage of this strategy is that it does not require any change in the standard drive system. Experimental results demonstrate the validity of the proposed technique [10].

ISSN: 2278 – 1323

Table 1: Evaluation of related work

Paper	Proposed Work	Evaluated Parameters for fault
A new remedial strategy for permanent magnet synchronous motor based on artificial neural network	Proposed model PMSM with stator winding turn fault and simulated on different testing data.	Analysis of the ratio of third harmonic to fundamental waveform obtained from Fast Fourier Transform (FFT) of magnitude components of the stator currents.
Automotive Internal Combustion Engine Fault Detection and Classification using Artificial Neural Network Techniques	Proposed SVSF is a estimation strategy, based on the sliding mode concept. It has been formulated to efficiently train ANNs.	defective lash adjuster, piston chirp, and chain tensioner problems by vibrations in crank.
Bearing fault detection using relative entropy of wavelet components and artificial neural networks	Simulated using a real motor current signal with addition of frequency components related to the bearing faults. They classified in two groups: normal and faulty signals with a high performance rate.	Particular frequencies at the stator current
Discrimination of stator winding turn fault and unbalanced supply voltage in permanent magnet synchronous motor using ANN	The ratio of third harmonic to fundamental FFT magnitude component of the three-phase stator	line current and supply voltage as a parameter for detecting stator winding turn faults under different load conditions
Dual neural classification for robust fault diagnosis in robotic manipulators	A Multilayer Perceptron (MLP) is employed to reproduce the dynamics of the robotic manipulator. Its outputs are compared with actual position and velocity measurements	The residuals of position and velocity

IV. PROPOSED SYSTEM

Artificial Neural Network (ANN): It will determine from that patterns given by statistical method that exactly fault is occurred or not. E.g. Component is faulty or not is exactly determined by ANN and then again this will provide to fuzzy system.

In this will going to use multilayer feed forward network with backpropagation algorithm. In multilayer network there is one input layer, one output layer and one or more hidden layers. Statistical methods output feeds to this module and it routes through inputs and will identify the accurate or exact fault present or not. Input for this is the behavior of parameters considered for fault detection over the time period. If behavior of parameter is same over the long period then accordingly it will take the decision of fault.

In the training cycle the user presents to the network a training pattern that contains a set of inputs and a set of desired outputs that corresponds to the inputs. Next, in prediction cycle, the network is supposed to be able to supply the user with output values corresponding to input values that it has never seen thanks to its generalization capability. A good generalization is generally a complex task where the training set contains sufficient information representing all cases so that a valid general mapping between outputs and inputs are found.

Steps in training and running a Perceptron:

1. Get samples of training and testing sets. These should include what the inputs x_i (observations) are Inputs and outputs generally should be normalized so that the largest number is 1 and the smallest is 0.

   This can be done with the basic formula

$$newInput = \frac{input - \min(\mathbf{inputs})}{\max(\mathbf{inputs}) - \min(\mathbf{inputs})}.$$

Here normalize Const would be 2 and offset Const would be 1 is we normalized from 0 to 1.

2. Set up the network
   1. Created input and output nodes
   2. Create weighted edges w_{ki} between each node. We usually set initial weights randomly from 0 to 1 or -1 to 1.
3. Run the training set over and over again and adjust the weights a little bit each time.
4. When the error converges, run the testing set to make sure that the neural network generalizes a good answer.

These steps can also be applied to the multi layer Perceptron.

Multilayer Perceptron Neural Network (MLP-NN):

The configuration of a multilayer perceptron with one hidden layer and one output layer. In this MLP each

ISSN: 2278 – 1323

neuron is connected to each neuron in the next layer. The output of the MLP is described by the following equation:

$$y_p = F_O\left(\sum_{j=0}^{N} w_{jp}^{H}\left(F_H\left(\sum_{i=0}^{N} w_{ij}^{I} x_i\right)\right)\right) \qquad (1)$$

$$\text{for p } = 1, 2 \ldots N$$

Where:

• wHjp represents the weights from neuron j in the hiddenlayer to the pth output neuron

• xi represents the ith element in the input layer

• FH and FO represent the activation functions in thehidden and output layers respectively.

• wIij are the weights from neuron i in the input layer tothe neuron j in the hidden layer.

The learning phase consists of the minimization of the cost function defined by:

$$E = \frac{1}{2}\sum_{p=1}^{N}(y_p - d_p) = \frac{1}{2}\sum_{p=1}^{N} e_p^2 \qquad (2)$$

B. Back propagation algorithm

The Back propagation algorithm is a simple gradient descend technique that minimizes the mean squared error defined in equation 2.The output of each neuron in the output layer is a function of the weights w. To minimize the cost function we must have:

$$\nabla E(w) = \frac{\partial E(w)}{\partial w_i} = 0 \qquad \text{for all } i \qquad (3)$$

The update rule in the back propagation algorithm is:

$$w(t+1) = w(t) + \nabla w(t) \qquad (4)$$

Where:

$$\nabla w(t) = -\eta \frac{\partial E(t)}{\partial w(t)} \qquad (5)$$

ANN has the ability to adjust its weights according to the differences it encounters during training.

The standard back propagation algorithms will going to use and algorithm as follows [13]:

1. First apply the inputs to the network and work out the output – remember this initial output could be anything, as the initial weights were random numbers.
2. Next work out the error for neuron X The error is What you want – What you actually get, in other words:
   $Error_X = Output_X (1-Output_X)*(Target_X - Output_X)$
   The "Output *(1-Output)" term is necessary in the equation because of the Sigmoid Function – if we were only using a threshold neuron it would just be (Target –Output).
3. Change the weight. Let W^{+}_{XY} be the new (trained) weight and W AB be the initial weight.
   $W^{+}_{XY} = W_{XY} + (Error_X * Output_Y)$
   Notice that it is the output of the connecting neuron (neuron Y) we use (not X). Need to update all the Weights in the output layer in this way.
4. Calculate the Errors for the hidden layer neurons. Unlike the output layer we can't calculate these directly (because we don't have a Target), so we Back Propagate them from the output layer. This is done by taking the Errors from the output neurons and running them back through the weights to get the hidden layer errors. For example if neuron X is connected as shown to Y and Z then we take the errors from Y and Z to generate an error for X.
   $Error_X = Output_X (1 - Output_X)(Error_Y W_{XY} + Error_Z W_{XZ})$
   Again, the factor "Output (1 - Output)" is present because of the sigmoid squashing function.
5. Having obtained the Error for the hidden layer neurons now proceed as in stage 3 to change the hidden layer weights. By repeating this method we can train a network of any number of layers.

V. RESULT AND DISCUSSION

	P1	P2	P3	P4	P5	P6	20% Fault	50% Fault	80% Fault
1	0.4494	0.32	0.18	0.25	0.6	0.7142	1	0	0
2	0.1798	0.21	0.14	0.2	0.13	0.1429	0	1	0
3	0.2022	0.25	0.16	0.2	0.18	0.2	0	1	0
4	0.1798	0.19	0.11	0.14	0.13	0.4286	0	0	1
5	0.1685	0.21	0.14	0.15	0.14	0.5143	0	0	1
6	0.1798	0.21	0.15	0.17	0.16	0.5143	0	0	1

Table 5.1 Data Normalization

P1, P2, P3, P4, P5 and P6 are the identified parameters on which fault of machine affected. Table 5.1 shows normalized form of all input and output parameters. Table 5.1 gives mapping or association between input and output parameters.

ISSN: 2278 – 1323

After completion of normalisation now in software need to choose all above parameters which shown in trial 1 and then analyse the working of chosen network.

Trial 1

- Network- Multilayer perceptron
- Inputs- 6
- Output- 3
- Learning rule- Backpropagation
- Hidden layer - 1 (with 5 neurons)

Trial No.	Hidden layer neurons	Error limit set	Learning rate	Iterations	completed	Mean square error
Trial 13	0	0.001	0.2	265	yes	0
Trial 14	0	0.001	0.3	235	yes	0
Trial 15	0	0.001	0.4	273	yes	0
Trial 16	0	0.001	0.4	255	yes	0
Trial 17	0	0.001	0.5	247	yes	0
Trial 18	0	0.001	0.5	260	yes	0

By doing many trials and testing, got the result that single layer perceptron neural network can detected fault for limited errors

VI. CONCLUSION

It is very important and necessary for today's critical machines in industry to provide detection for fault which will improve efficiency as well as productivity without consuming time or without stopping any kind of work. For decision making identified artificial neural network.

This single layer perceptron neural network can detected fault for limited errors. Similarly we can use the neural network for detecting the more number of attributes with more complex network. It is also possible to predict fault by using hybrid model like Neuro-Fuzzy.

.

ACKNOWLEDGMENT

I am very thankful to the Savitribai Phule Pune University, Pune. I am highly grateful to my department and college, Department of computer engineering and Smt. Kashibai Navale College of Engineering to providing all the facilities.

I am thankful to my esteemed guide Prof. S. K. Pathan for expert and precise guidance.

REFERENCES

[1] Chaochao Chen, Bin Zhang, and George Vachtsevanos, "Prediction of Machine Health Condition Using Neuro-Fuzzy and Bayesian Algorithms," in IEEE transactions on instrumentation and measurements, vol. 61, no. 2, pp. 567-577 February 2012.

[2] William Hand Allen and Ahmed Rubaai, "Fuzzy-Neuro Health Monitoring System for HVAC System Variable-Air-Volume Unit", in IEEE IACCA,vol.289, pp. 019-027, May 2013.

[3] Chaochao Chen, Bin Zhang, George Vachtsevanos, "Neuro–Fuzzy and High-Order Particle Filtering" in IEEE transactions on industrial electronics, vol. 58, no. 9, pp. 4353-4364, September 2011.

[4] Chafaa, K., Slimane, N. , Boutarfa, A. " Fault diagnosis in robotic manipulators using artificial neural networks and fuzzy logic" in Computer Applications and Information Systems (WCCAIS),World Congress, vol. 45, pp. 1-6, January 2014.

[5] Montes Dorantes, P.N. ; Nieto Gonzalez, J.P. ; Mendez, G.M. "Fault Detection Systems via a Novel hybrid Methodology for Fuzzy Logic Systems based on Individual base inference and Statistical Process Control",in Latin America Transactions, IEEE (Revista IEEE America Latina), vol.12, no.4, pp. 706-712, June 2014.

[6] Marcal, R.F.M. and Hatakeyama, K., "Expert System based on fuzzy rules for monitoring and diagnosis of operation conditions in rotating machines", in Management of Engineering & Technology (PICMET), Portland International Conference, vol. 788, pp. 577 – 584, July 2014.

[7] ZeFeng Wang, Zarader, J.-L., Argentieri, S. "Aircraft fault diagnosis and decision system based on improved artificial neural networks" in Advanced Intelligent Mechatronics (AIM), IEEE/ASME International Conference, vol. 234, pp. 1123 – 1128, July 2012.

[8] Jian-Da Wu and Li-Hung Fang, "A Fault Diagnosis System for a Mechanical Reducer Gear-Set Using Wigner-Ville Distribution and an Artificial Neural Network" in Computational Science and Its Applications (ICCSA), 13th International Conference IEEE, vol. 465, pp. 170-173, June 2013.

[9] Hooshmand, R.A., Parastegari, M. and Forghani, Z., "Adaptive neuro-fuzzy inference system approach for simultaneous diagnosis of the type and location of faults in power transformers", in Electrical Insulation Magazine, IEEE, vol.28, no.5, pp. 32 – 42, August 2012.

[10] Greety Jose and Victor Jose, "Fault diagnosis in induction motor using soft computing technigues", in International Conference on Advanced computing and communication systems IEEE, vol. 365,pp. 876-882, December 2013.

[11] Adouni, A., Ben Hamed, M., Flah, A. and Sbita, L., "Sensor and actuator fault detection and isolation based on artificial neural networks and fuzzy logic applicated on induction motor" in Control, Decision and Information Technologies (CoDIT), International Conference,vol. 467, pp. 917-922, May 2013.

[12] Rahman, R.Z.A., Yusof, R. and Ismail, F.S., "Model-based fault detection and diagnosis optimization for process control rig" in Control Conference (ASCC), 9th Asian, vol. 589, pp. 1-6, June 2013.

[13] https://www4.rgu.ac.uk/files/chapter3%20-%20bp.pdf

ISSN: 2278 – 1323