

IMPLEMENTATION OF ARTIFICIAL INTELLIGENCE FOR DIAGNOSIS OF THE FAULTS OF MOTOR-FAN SYSTEM

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ABSTRACT

Reliable diagnostic methodologies for motor-fan system need to cost effective based maintenance. Several techniques are currently available to fault diagnosis. Some of these techniques cannot determine the fault type quickly and accurately as required. Thus, there is an essential need to use new techniques to achieve quick, easy and highly reliable decisions. Artificial intelligence increasingly used in fault diagnosis systems. In this paper Neural Networks, Fuzzy Logic System, Neuro-Fuzzy System and Adaptive Neuro-Fuzzy Inference used as new artificial intelligence techniques to develop automated fault classification tools. Neural networks classifiers used for discriminant faults spectra based on batch training techniques. Fuzzy logic system identifiers used for adding a logical nature to the fault detection process. Fuzzy logic application extended to hybrid neuro-fuzzy system with greater accuracy due to parallel processing of data both numerical and logically. Finally, adaptive neuro-fuzzy inference system technique adding a logical nature to the fault detection process.

KEYWORDS: *Motor-fan system, neural network, fuzzy logic system, neuro-fuzzy system, adaptive neuro-fuzzy inference system*

INTRODUCTION

Yagulo, et al., (2007), in their work emphasize diagnosis of rotating machinery faults has become highly specialized. Maintenance actions planned to take place at a time convenient to man and machine.

Fault diagnosis requires a system that detects and identifies the component or process that causes the deviation from the normal. Fault diagnosis has several techniques mostly depending on vibration analysis.

F. R. Gomaa, et al., (2016), in their work the vibration spectra of many machines usually provide enough information about the fault in progress both qualitatively and quantitatively.

Yang, et al., (2002), in their work some of those vibration analysis techniques cannot determine the fault type quickly and accurately as required, so that there is an essentially great need to use new methodologies to achieve quick,

easy and high accuracy decisions. Artificial Intelligence (AI) is a successful method increasingly used in fault diagnosis systems due to its accurate results, easy and quick in used.

Yasir (2017) use intelligence systems include several techniques such as neural network (NN), fuzzy logic system (FLS); genetic algorithms (GA), Adaptive Neuro-Fuzzy Inference System (ANFIS) and support vector machine (SVM) have previously developed many different methods.

D. Grzechca, et al., (2002), in their work NN and FLS used for identification faults. Neural networks are very useful predictors due to their properties and capabilities. They pose features that have uniformity in analysis and design, easy of handling, functional dependency and insensitivity to noise or unreliability in the data.

NN proposed in, Dan W. (1998), to solve the fault diagnosis problem. A neural dictionary created for go/no-go testing. FLS used for transformation of measuring vector to zero-one range.

As explained in, P. V. Goode, et al., (1995), NN and FLS for incipient fault diagnosis in induction motor and mechanical components. They achieved 100% detection accuracy and they prove well suitable for real time application.

K. Kim, et al., (2002), in their work neural networks used to study the faults of an induction motor and the mechanical components of the machine with different rating by changing the load on the motor and training the data to make classification of untrained-upon data with different rating of motor and the mechanical components of the machine.

Fuzzy logic system used in fault diagnosis of electrical machines and derives, as in Jia-zhou, et al., (2000). FLS chosen as a suitable diagnostic technique for fault performance engine to build an input dataset.

Mihari, et al., (1997) in their work an integrated fuzzy system presented for diagnoses the faults that occur in transmission network and substations. False operations or non-operations of protective devices discrimination the fault identification schemes, analyzing through fuzzy inference process done.

Jihene et al., (2002) determined the knowledge that depending on fault detection and diagnosis described for reasoning from the analytic. NFS methodologies provided with focus on combination between neuro-fuzzy network and neural logical operator.

Leocundo, et al., (2003), in their work a neuro-fuzzy used to design fuzzy rule base of intelligence system. ANFIS technique used for building fuzzy model to control stepping motor drive. Evaluation of the tracking properties and fuzzy logic controller capacities tested.

In the presented work, a diagnostic tool (NN, FLS, NFS and ANFIS) developed to automate fault detection process. Fault identification process gave accurate results with neural networks and neuro-fuzzy techniques than the fuzzy logic system and ANFIS techniques.

Moto-Fan System

The motor-fan system contain motor, two flexible couplings, shaft, gearbox and fan as appeared in Fig. 1. Faults of motor-fan system can divide to electrical and mechanical faults. Electrical faults at the motor supporting method and interior rotor motor components. The mechanical faults appeared in gearbox supporting system, gearbox bearing and gear components, unbalancing of the fan blades, losing some bolts of the coupling, and misalignment connections between gearbox axis, motor axis and transmission shaft.

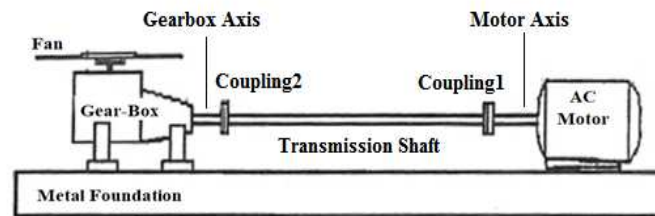


Figure 1: Motor – Fan System.

Using Neural Networks (NN) for Fault Diagnosis of Motor-Fan System

Three types of neural networks used for detecting motor-fan system defects. Perceptron, self-organizing (SON) and learning vector quantization (LVQ) networks. The theory of neural network technique can explain as following;

Neural Network Structure

NN defined as set of interconnected simple units that execute parallel to perform a common global task. Units undergo learning process to automatically update network parameters in response to possibly evolving input environment. NN has capability to organize its structural constituents, also able to learn from their environment to improve performance in some sense, Bob Sutton (2009).

The popular approach to develop NN based diagnostic systems is to induce several faults into specific machinery sub-components

Neural Networks are software tools designed to estimate relationships in data and analysis of these data for classification, identification and fault diagnosis, as explained in Mohri et al., (2013). NN used to diagnosis the faults of motor-fan system. Emphasis is on perceptron network, Self-Organizing Network (SON) and Learning Vector Quantization (LVQ) network due to their reasonable performance, accuracy in classifying patterns and ease of training. The architecture of the three used networks can summarized as following;

Perceptron Network

Perceptron network is an algorithm for learning binary classifier that called threshold function, as discussed in Saadatdoost et al., (2011). Perceptron network for two inputs and one output consists of basic elements shown in Fig. 2:

- Input signals (P_1, P_2)
- Connecting links (which are characterized by weight of its own (w))
- (b) bias
- Summing junction (Σ)
- (f) transfer function
- (a) output

Scalar input multiplied by scalar weight to form (WP), one of the terms that is sent to the summing. The other input, 1 multiplied by bias (b) and based summing. The summing output (n) referred to net input, goes into transfer function to produce scalar neuron output.

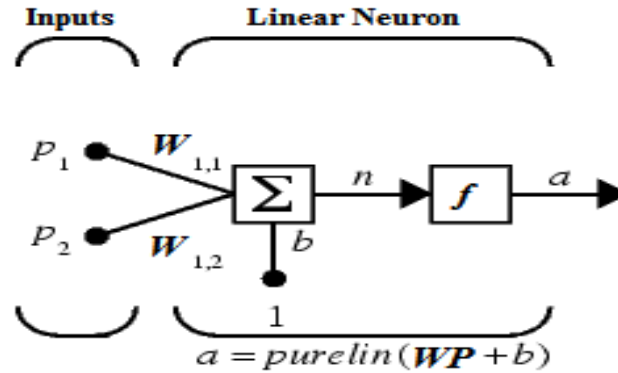


Figure 2: Two Inputs and Single Output Perceptron Network.

Self-Organizing Network (SON)

Luiza Mici, et al (2018) in their work explained the self-organizing network as a trained network unsupervised learning used to produce low dimensional (typically two-dimensional) of input space of training samples. It is method used to do dimensionality reduction. Self-organized network learning discovers significant patterns or features in the input data. SON algorithm provided with set of local nature rules, which enables it to learn and compute input and output mapping with specific desirable properties, Muhammed Fahad et al., (2007).

The structure of SON like in Fig. 3 contain input layer (source), output layer (representation), feed forward connections input to output and lateral connections between neurons output layer.

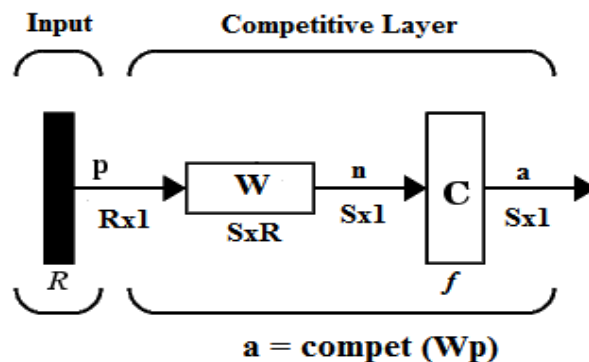


Figure 3: Self-Organizing Network Structure.

Learning Vector Quantization (LVQ)

The LVQ network, M. T. Hagan et al (2000), use unsupervised and supervised learning classification. LVQ network learning combines competitive learning with supervision. It is requiring a set of target output, target vector only have zeros

except for a single which indicates class of input vector. Neurons in first layer assigned to an output neuron and this generates the matrix (W^2) as show in Fig. 4.

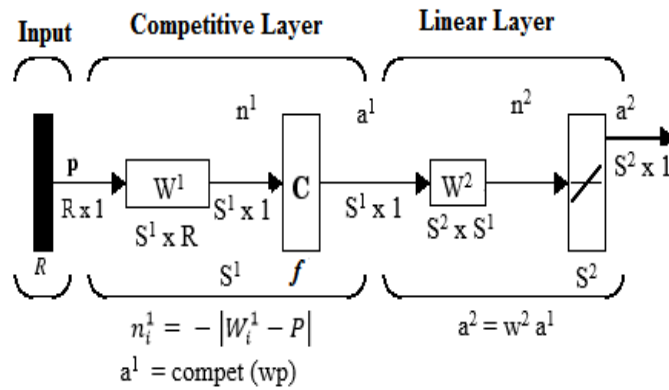


Figure 4: Learning Vector Quantization Network Structure.

Design Technique of Neural Networks for Motor-Fan System

The design of any type of neural network involves three phases, initialization, training and simulation phase. In initialization phase, the neural network initiated by determining number of inputs and target output points. The learning and training network are the main phase in the neural network design. Learning rule used to train the network to perform required task, Simon Haykin (2009). Then the simulation phase used to classify fault types for new data.

In simulation phase, when input pattern detected at the input, its output becomes current output. If the input pattern does not belong to list of input patterns, the classification rule will not be able to determine the type of fault.

Neural networks must identify and discriminate faulty operation employing the commonly used frequency-amplitude vibration signature plot, Helge Ritter et al (1992). Those amplitudes are the input vector to the networks. Fig. 5, 6 and 7 explain the structure of the neural network with inputs, outputs and design phases.

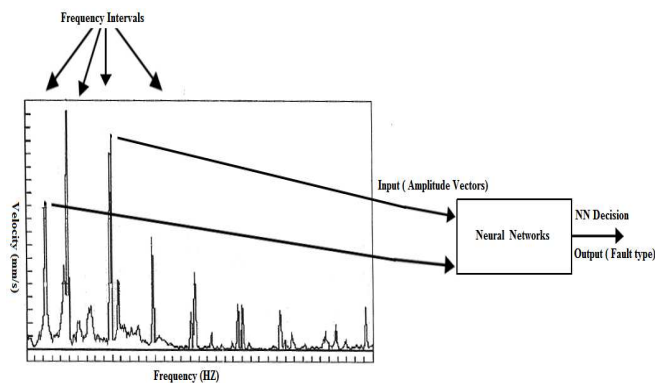


Figure 5: Neural Network Inputs and Outputs.

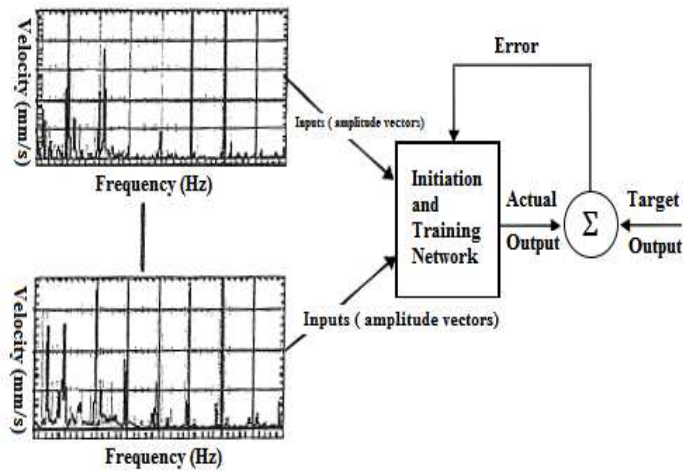


Figure 6: Initialization and Training Phases of the Neural Network.

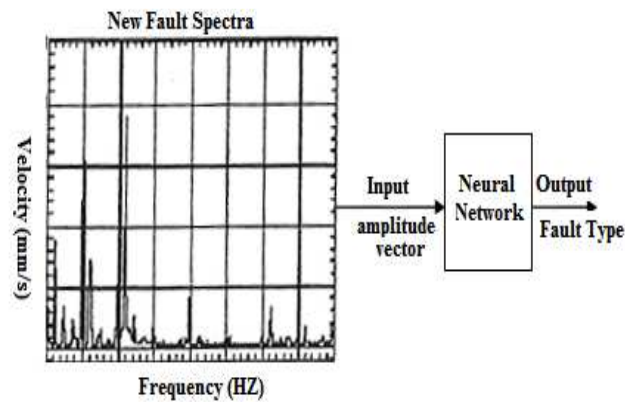


Figure 7: Fault Diagnosis for New Data (Simulation Phase).

Diagnosis Faults of Motor-Fan System Using Fuzzy Logic System (FLS)

Fuzzy Logic System Architecture

FLS structured model-free estimator to approximate function through linguistic input and output associations, Bart Kosko (2000). It can implement in software. Four main parts of fuzzy logic system shown in Figure 8.

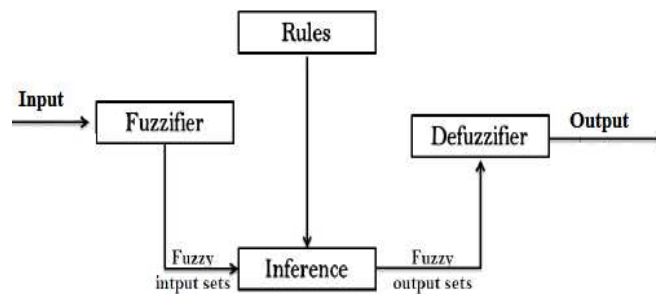


Figure 8: Fuzzy Logic System Architecture.

Fuzzification, transforms the system inputs into fuzzy sets. **Knowledge Base**; stores IF-THEN rules.

Inference Engine; process through inputs fuzzy inference and IF-THEN rules.

Defuzzification, transformation inference engine fuzzy set into crisp value.

Fuzzy System Identification

Fuzzy system designed to increase decision reliability. FLS used to investigate the faults types of the motor-fan system. A fuzzy logic designed to increase decision reliability, Heung J. L. et al (2000). FLS use for diagnose faults of the input amplitude of the motor-fan system data spectra, and the output were the FLS decision which is scaled (0), (1) for faults and no faults respectively as in Fig. 9.

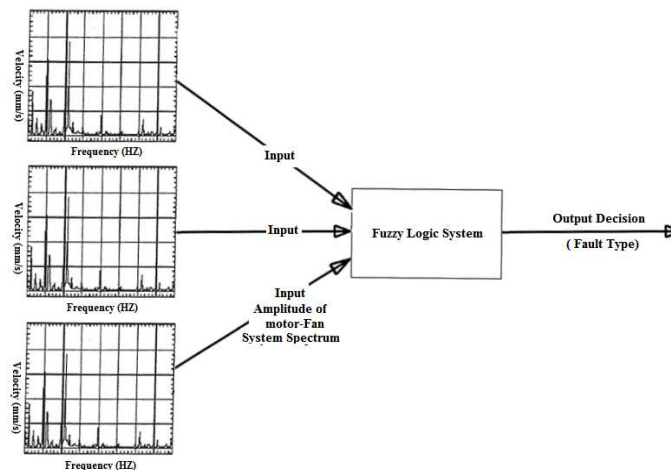


Figure 9: FLS Scheme of Motor-Fan System Faults.

Neuro-Fuzzy System (NFS) for Moto-Fan System Faults Detection

P. V. et al., (1999) in their work they define the neuro-fuzzy system as intelligence system. NFS synergizes two techniques neural network and fuzzy logic. It combining human-like reasoning style from fuzzy systems and learning of connectionist structure from neural networks.

NFS used for motor-fan system to confirmed the NN decision. It works when the motor-fan system spectrum interned to neural network to get the output which be fault type that checked by interning again to the FLS to conform this fault by yes or no as output of FLS as shown in Fig. 10.

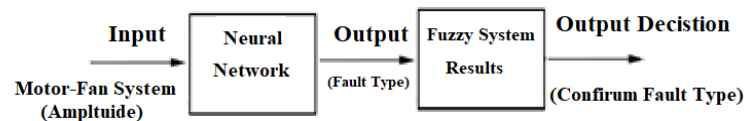


Figure 10: NFS Structure.

Fault Diagnosis of Motor-Fan System Using ANFIS and NFS

(ANFIS) adaptive neuro-fuzzy inference system is artificial neural network that based on Takagi-Sugeno fuzzy inference system. It offered a reliable way to pinpoint fault cases qualitatively as well as quantitatively. From Fig.

11, the system has two adaptation layers (1 & 4). First layer with three adjustable premise parameters related to input membership functions. Three adjustable conclusions parameters related to the first-order polynomial included in Fourth layer, Jie-Sheng et al (2015).

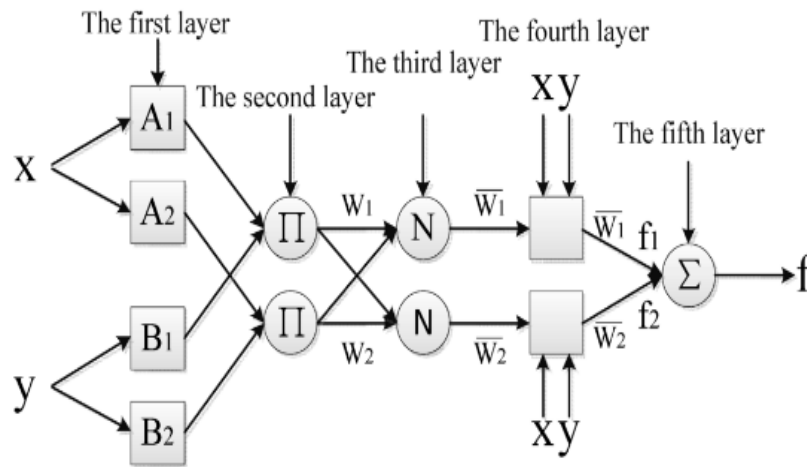


Figure 11: Typical ANFIS Structure Diagram.

ANFIS, which used in this research to study its ability to use in fault classification and to study its performance by comparing its output results with other techniques

Software Development

A MATLAB based software designed to automate data preparation, drawing motor-fan system spectra that used for input to the networks, training, and simulation processes of the network. Four windows designed as in Fig. 12 (a, b, c and d), first window is the introduction window, second window is the motor-fan system window, third window is the general case window where important frequencies for any machine can be calculated and its spectrum can be drawn. The fourth and final window is the fault identifications window, which uses all techniques presented in this paper to identify the fault type for any machine.

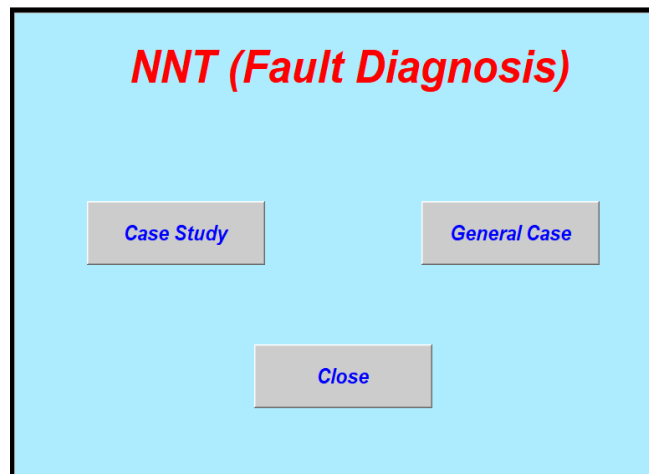


Figure 12 (a): Neural Network Fault Diagnosis Window.

The screenshot shows a software interface with two main data entry sections. The top section is titled 'INPUT DATA' and contains two columns: 'Frequency(HZ)' and 'Amplitude(mm/s)'. Below this is a 'Prepare Data' section with identical columns. To the right of these sections are several input fields labeled 'First', 'Step', 'Final', and 'Length of y', along with a button labeled 'NNT'. There are also two large empty rectangular areas on the right side of the window.

Figure 12 (b): Motor-Fan System Window.

This screenshot displays a comprehensive form for entering system parameters. It is organized into several sections: 'Motor Information' (Motor Speed, Motor Power, No. of Motor Phase, Slip Motor Frequency, Motor Frequency), 'Bearing Information' (Pitch Diameter, Roller Diameter, Contact Angle, No. of Rollers, BPFO, BPFI, FTF, RPS), 'Gear Information' (No. of Teeth, Teeth Meshing Frequency), and 'Fan Information' (No. of Fan Blades, Fan Frequency, Misalignment, Unbalance). A 'Data' section on the right includes 'Frequency' and 'Amplitude' columns and a 'Length of Spectrum' field. At the bottom right, there are 'Calculate' and 'Spectrum' buttons, and a 'Fault Identification' button.

Figure 12 (c): All the Motor-Fan System Faults.

The screenshot shows a 'Fault Identification' window. It features a 'No. of Training Files' input field and a grid of 'Inputs'. Below this, there are two main sections: 'Neural Networks' and 'Fuzzy Logic + Neuro_Fuzzy'. The 'Neural Networks' section includes options for 'Perceptron', 'SON', and 'LVQ', along with 'No. of Checking Files', 'Percentage %', and 'Fault Type' fields. The 'Fuzzy Logic + Neuro_Fuzzy' section includes options for 'Fuzzy' (with sub-options UN, MA, LO, BE) and 'Neuro-Fuzzy', and 'ANFIS' options for 'Anfis1' and 'Anfis2'.

Figure 12 (d): Fault Identification Window.

CONCLUSIONS

The presented paper aimed at developing an efficient technique for fault diagnosis of moto-fan system. Neural network, fuzzy logic system and neuro-fuzzy systems implemented a new artificial intelligence approach in motor-fan system fault detection. The amplitude of vibration spectra of moto-fan system used to determine the fault type. A MATLAB code designated to structure neural networks (perceptron, SON and LVQ), fuzzy logic system and neuro-fuzzy system also. Four windows designed also for joining all the inputs (motor-fan system spectrums), outputs (fault type) and detection techniques. The main conclusion of the presented work can explain as following;

- Perceptron networks offer an easy and quick fault detection tool on the expense of prediction accuracy. This technique should only use in preliminary phases of the fault detection process, due to its limitation in classifying nonlinearly separable data.
- Self-organizing and learning vector quantization networks can be efficiently used in fault detection process. These techniques showed robustness and accuracy in fault identification process.
- Fuzzy logic system identifiers successfully managed to inspect spectra in human-like way. However, such technique loses the power of numerical interpretation of data. As a result, wrong fault predictions observed in those cases where logical rules qualitatively overlapped.
- Neuro-Fuzzy approach for fault detection offered a reliable way to pinpoint fault cases qualitatively as well as quantitatively. This technique is free from those drawbacks observed in NN and FLS identifiers indicated above. In short, neuro-fuzzy system identifiers accomplish logical as well as numerical power in processing measurement spectra resulting in greater fault detection accuracy.
- Adaptive Neuro-Fuzzy Inference Systems have strong limitations with today's processing power when dealing with a large amount of data.

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