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Neural Network and Fuzzy Logic Diagnostics of 1x Faults in Rotating Machinery

In this paper, the application of neural networks and fuzzy logic to the diagnosis of faults in rotating machinery is investigated. The learning-vector-quantization (LVQ) neural network is applied in series and in parallel to a fuzzy inference engine, to diagnose 1x faults. The faults investigated are unbalance, misalignment, and structural looseness. The method is applied to a test rig (Hassan et al., 2003, ASME Paper No. GT 2003-38450), and the effectiveness of the integrated Neural Network and Fuzzy Logic method is illustrated. [DOI: 10.1115/1.2227417]

Introduction

Maintenance management of industrial facilities is a major task for all manufacturing companies. Investments of billions of dollars in capital equipment have to be maintained to preserve company assets and to ensure continuous production [1,2]. This fact has been recognized for a long period of time, but lately it became apparent that it is necessary for a maintenance management program to also reduce inflated maintenance costs and to improve operator safety [3–5].

Condition-based maintenance (CBM) has evolved to be the leading methodology to effectively plan for the required maintenance activities. This is the premise of the technologies of predictive maintenance [1], where the maintenance or repair action is based on the condition of the machine, i.e., only needed maintenance work is done, thus reducing maintenance costs and improving productivity [6]. However, for this technique to be effective, machinery condition should be measured and competently analyzed to support the appropriate maintenance decision [3,7,8].

Currently, in order to apply CBM, the condition of plant assets is determined by human experts, with the support of technologies such as vibration spectral measurements. The expert opinion is then somehow incorporated in the maintenance management system. Several attempts at automating the spectral analysis process by rule-based expert systems and inference engines in the late 1980s and early 1990s provided some products that are available in the market for providing recommendations mainly based on spectral analysis. These products are available from most condition monitoring equipment manufacturers, but were not quite successful in the market, because most of the time the user can provide a better recommendation than the expert system [1].

Possibilities exist nowadays for replacing the rigid rule base of expert systems with fuzzy logic, which would have the advantage of approaching human thinking. Moreover, the current availability of great computational capabilities should also be exploited. This is the objective of this paper. Actually, a condition monitoring professional may inspect the frequency spectrum of the vibration signal and decide whether the machine is in normal operation or a specific fault is in progress. In doing so, both numerical analysis represented by the equipment used to analyze the signal, and logic analysis represented by the human experience and reasoning, are used throughout the diagnostic process. It is thus clear that the process relies on the availability of the numerical capabilities as well as the professional analysts to perform the diagnosis task. This is a limitation for many industrial facilities. Issues like availability, cost, and reliability of the process should be investigated before employing a predictive maintenance program. The effort in this paper is directed towards the automation of the diagnostic procedure to incorporate both numerical and logic analyses, which minimize the need of human expertise that can be transmitted to the logic module of the diagnostic system [9].

This paper focuses on the advantage of the relatively modern techniques such as neural networks and fuzzy logic systems to improve the rotor-bearing fault diagnostic procedure. Using both techniques in a hybrid system should have the advantage of the fast and efficient numerical capabilities of neural networks as well as the flexibility and the logic inference of fuzzy systems [10,11].

The neural network provides suggestions about the type of fault suspected, while a fuzzy logic module is designed to focus on the amplitude spectrum characteristics of that particular fault, both as a stand-alone diagnostic tool and as an in-series diagnostic tool with the neural network.

Introducing logic in the diagnostic process gives the procedure the power of fast and complex computations represented by the neural network performance, in addition to the flexibility and reasoning of the fuzzy systems. This configuration suits the diagnostic procedure of a vibration specialist who uses equipment for data processing and reasoning resulting from her/his experience.

Background

A neural network (NN) is a biologically inspired computational model that consists of processing elements (neurons) and connections between them, as well as of training and recall algorithms. The structure of a neuron is defined by inputs, having weights bound to them; and an input function, which calculates the aggregated net input signal to a neuron coming from all its inputs; and an activation (signal) function, which calculates the activation level of a neuron as a function of its aggregated input signal and (possibly) of its previous state. An output signal equal to the activation value is emitted through the output of the neuron. NNs are owing to the main role of the connections. The weights bound to them are a result of the training process and represent the “long-term-memory” of the model [12]. The main characteristics of a NN are:

- Learning: a NN can start with no knowledge and can be trained using a given set of data examples, that is, input-output pairs (as in supervised training) or only input data (as in unsupervised training). Through learning the con-

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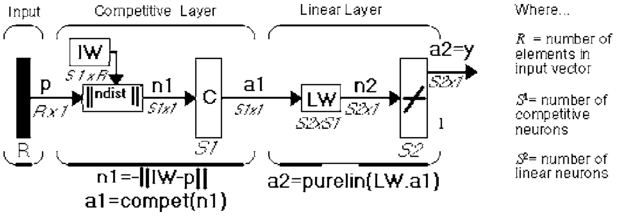

Fig. 1 LVQ neural network

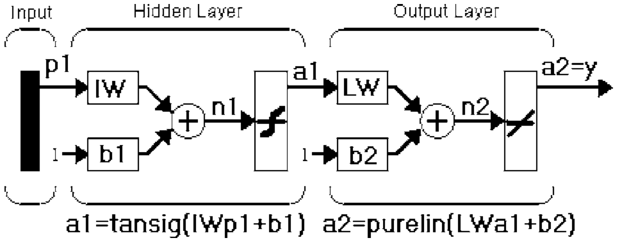

Fig. 2 Feed forward network

nection weights change in such a way that the network learns to produce desired outputs for known inputs.

- Generalization: if a new vector that differs from the known examples is supplied to the network, it produces the best output according to the examples used.
- Massive potential parallelism: during the processing of data many neurons "fire" simultaneously.
- Robustness: if some neurons go wrong, the whole system may still perform well.

One way to represent inexact data and knowledge, closer to humanlike thinking, is to use fuzzy rules instead of exact rules when representing knowledge. Fuzzy systems are rule-based expert systems based on fuzzy rules and fuzzy inference. Fuzzy rules represent in a straightforward way the common sense knowledge and skills, or knowledge that is subjective, ambiguous, vague, or contradictory [11,13]. Common sense knowledge may have been acquired from long term experience, from the experience of many people, over many years. A fuzzy system is defined by three main components:

1. fuzzy input and output variables,
2. a set of fuzzy rules, and
3. fuzzy inference mechanism.

Neural Networks Architecture

The availability and customization of the NN to fit the problem at hand was investigated in our previous work [14]. Five networks were investigated (perceptrons, linear, feed forward, self organizing, and learning-vector-quantization (LVQ)), and two networks of those previously investigated were chosen as promising networks (feed forward and LVQ) [14]. In this current work, the procedure and developed standard techniques for the diagnosis process using neural networks are extended.

The LVQ neural network provided the best performance, as demonstrated from our previous experiments [14] (see Fig. 1). Therefore we selected the LVQ network to be used in our elaborate tests as a diagnostic tool. However, the LVQ network has a shortcoming: it cannot distinguish multiple faults. As it uses a competitive layer in its input layer so it could not classify any combined faults (more than one fault in the same amplitude spectrum), there is always only one winner [15,16]. Each type of fault is represented by one neuron in the competitive layer; the characteristic of the competitive layer is that all the neurons' output is equal to zero except only one neuron output is equal to one, which is the winner neuron and represents a single fault.

Due to the incapability of the LVQ network to detect more than one fault, we used also the feed forward network due to its high flexibility to detect and classify more than one fault in the same amplitude spectrum [17]. However, the performance of the feedforward network was modest in our earlier experiments [14]. Therefore to enhance the performance of the feed forward network (Fig. 2) we implemented some modifications to its previously used architecture, as follows:

- Two hidden layers were used instead of one with a large number of hidden neurons [14,17].
- The output layer function was changed from pureline function to logsig function and the output layer neurons were augmented from one neuron to four neurons [14,15].
- The training algorithm was changed from the Levenberg-Marquedt (LM) training algorithm (trainLM) to the Resilient Propagation (RP) training algorithm (trainRP), which is much faster, especially with a large number of neurons [14,18].

New Sets of Experiments

In order to satisfy the requirements of the training and testing of the neural network fuzzy logic parallel and series configurations a new set of experiments was carried out. Twelve sets of experiments were implemented; this was carried out by planting each fault separately first into the test rig. Each set was for a different fault or fault level; nine sets of vibration signatures of the machine train were acquired for each fault class separately.

Measurements were performed on the five-disc test rig [14]. A Bruel & Kjaer (B&K) 2526 data collector was used. Data acquisition is handled by Sentinel software in which measurements are analyzed and, if satisfactory, stored in a Matlab-friendly format ready for the application of the neural network or fuzzy logic application. The measurement process is illustrated in Fig. 3. The following are selective data settings [19]:

- Test rig speed: 1800 rpm.
- No. of samples: 400 sample.
- Amplitude unit: mm/sec rms (velocity).
-

$$\begin{aligned}\text{Frequency interval } \Delta F &= \frac{\text{Windowing factor} * \text{Frequency span}}{\text{Number of lines}}\\ &= \frac{1.5 * 200}{400}\\ &= 0.75 \text{ Hz}\end{aligned}$$

- Resolution $=2*\Delta F=1*0.75=1.5$ Hz

The following setup for the B&K 2526 data collector was used [19]:

- For overall measurements:

  High pass filter=10 Hz
  Averaging time=5 s
  Detector rms
  Integration one (acceleration to velocity)
  Upper limit=1 KHz
  Transducer (accelerometer) sensitivity 1 Pc/m/s^2
  Amplitude scaling=linear

- Auto spectrum measurements:

  Frequency span=200 Hz
  High pass filter=3 Hz
  Averages=4 times

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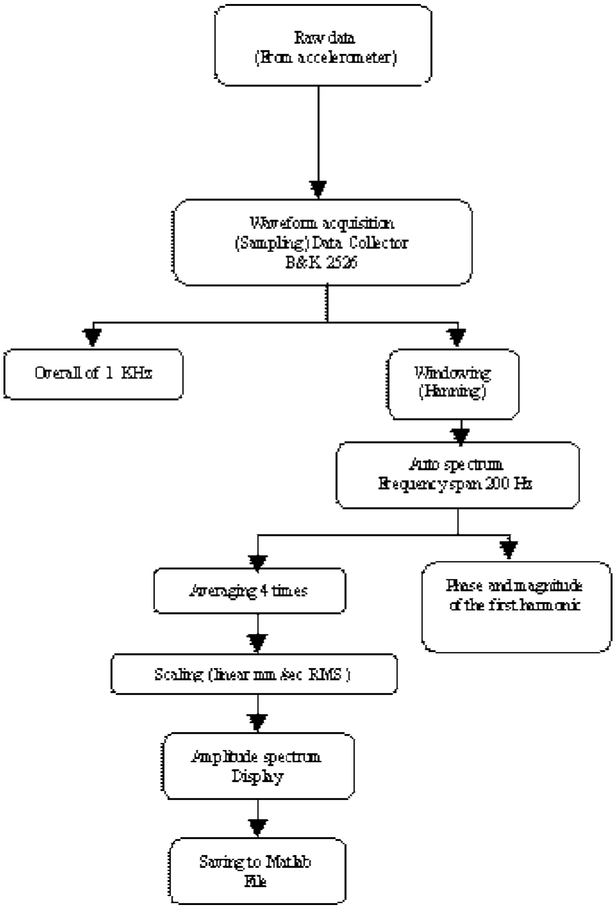

Fig. 3 Flow chart of measurement procedure

Averaging mode=spectrum
Windowing mode=Hanning window
Detector RMS
Integration one (acceleration to velocity)

Fault Planting. Neural networks and fuzzy logic should be trained and tested by data obtained by planting faults that need to be later identified by the LVQ, feed forward networks [16], and the Sugeno fuzzy inference system [20,21]. Twelve cases are considered here, no-fault, mechanical imbalance (two levels), structure looseness (two levels), bearing looseness (two levels), angular misalignment (two levels), parallel misalignment (two levels), and combined misalignment (one level). See Fig. 4 for fault implementation on test rig.

Acquired Data Sets. Nine data sets were collected for each of the previous discussed 12 classes. Each data set consists of 11 data files; each data file represents 400 samples of the amplitudes of a 200 Hz amplitude spectrum measured at a certain point on the machine train. Each data file is a vector of 1 column and 400 rows; these data files were transferred to MatLab files so they can be handled by the neural networks and the fuzzy inference system. Each set of 11 data files was measured at a predetermined measurement point location and direction on the machine train as follows:

1. Motor non drive end bearing horizontal direction (MNDE-H)
2. Motor non drive end bearing vertical direction (MNDE-V)
3. Motor drive end bearing horizontal direction (MDE-H)
4. Motor drive end bearing vertical direction (MDE-V)
5. Motor drive end bearing axial direction (MDE-A)

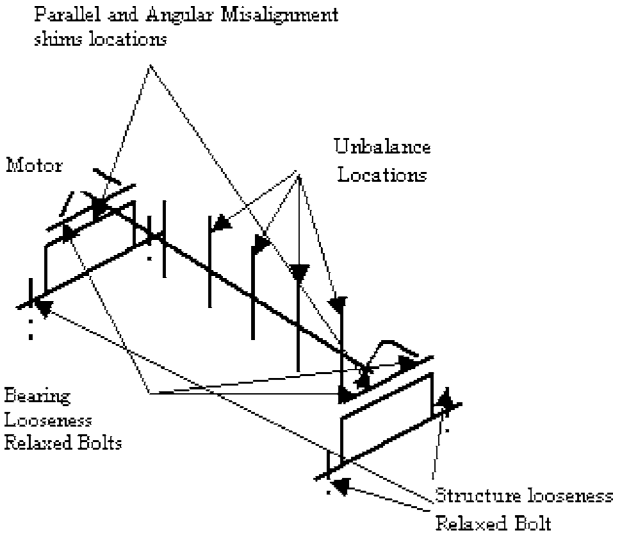

Fig. 4 Fault implementation on test rig

6. Drive end bearing horizontal direction (DE-H)
7. Drive end bearing vertical direction (DE-V)
8. Drive end bearing axial direction (DE-A)
9. Non drive end bearing horizontal direction (NDE-H)
10. Non drive end bearing vertical direction (NDE-V)
11. Non drive end bearing axial direction (NDE-A)

Files are split into two groups; the first group is used for training the networks, while a second group is used for validation of the trained networks. This technique is common in designing neural networks where the network performance is tested by data that have not been used for training to guarantee generalization.

Neural Networks Training and Testing Results

Each of the LVQ and the feed forward networks were trained and tested for validation by different data files; the files used for validation were not used for the training of the networks. The following results were obtained for each network:

LVQ Network

Total training performance: 100% correctly trained
No fault training results: 100% correctly trained
Unbalance training results: 100% correctly trained
Looseness training results: 100% correctly trained
Misalignment training results: 100% correctly trained

Total validation performance: 100% correctly identified
No fault validation results: 100% correctly identified
Unbalance validation results: 100% correctly identified
Looseness validation results: 100% correctly identified
Misalignment validation results: 100% correctly identified

It should be noted that training performance goal was met after 150 training epochs (see Fig. 5). The maximum number of epochs for training that was permitted to achieve the goal was set to 500 epochs, so the network reached its goal within the permitted number of epochs. This maximum number of epochs can be adjusted. The network succeeded in reaching its performance goal within a reasonable number of epochs.

Feed Forward Network

Total training performance: 100% correctly trained
No Fault training results: 100% correctly trained
Unbalance training results: 100% correctly trained
Looseness training results: 100% correctly trained
Misalignment training results: 100% correctly trained

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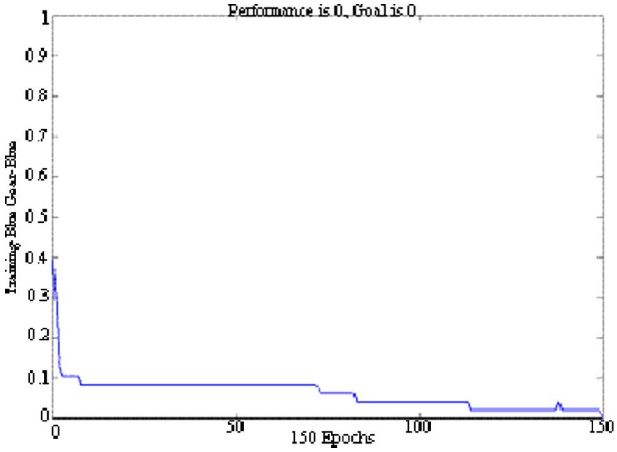

Fig. 5 Training of LVQ network

Total validation performance: 94.7% correctly identified
No Fault validation results: 100% correctly identified
Unbalance validation results: 100% correctly identified
Looseness validation results: 75% correctly identified
Misalignment validation results: 100% correctly identified

Note that the training performance goal was not met, training stopped after 27 training epochs due to reaching the minimum gradient (see Fig. 6).

The above results clearly show the success of the neural networks both in training (to become capable of diagnosing) and of really doing the diagnosis (validation). In fact, because the training and validation data sets are independent, and because our implementation of all faults at two different levels (see previous section), it is quite remarkable the success of the neural networks, particularly the LVQ Network, in identifying the faults from an array of possible faults and fault levels.

Fuzzy Logic Applied to Diagnostic Systems

Fuzzy sets were introduced by Zadeh in 1965 to represent or manipulate data and information possessing nonstatistical uncertainties [22]. It was specifically designed to mathematically represent uncertainty and vagueness and to provide formalized tools for dealing with the imprecision intrinsic to many problems [23]. Fuzzy logic provides an inference morphology that enables approximate human reasoning capabilities to be applied to knowledge-based systems. The theory of fuzzy logic provides a mathematical strength to capture the uncertainties associated with human cognitive processes, such as thinking and reasoning [24].

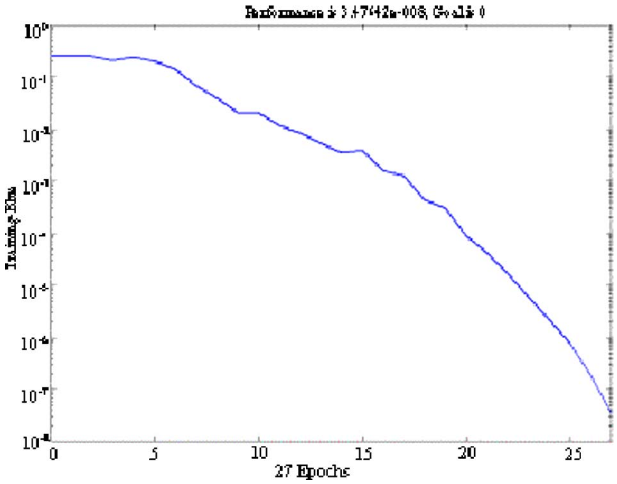

Fig. 6 Training of feed forward network

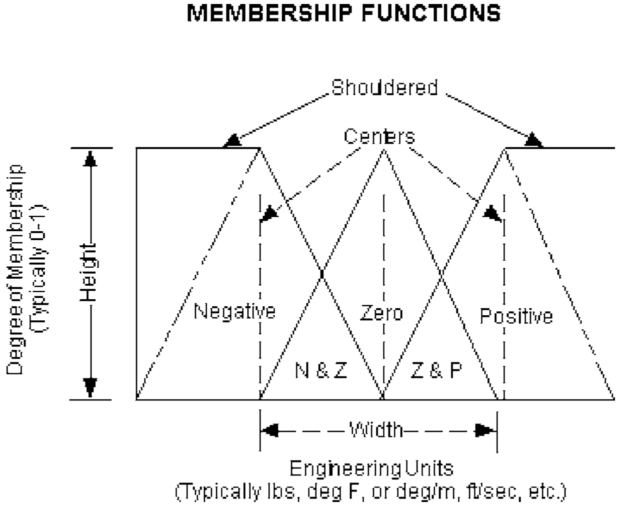

Fig. 7 The features of a membership function [20]

Definition of a Fuzzy Set. Fuzzy set A in X is characterized by its membership function

$$\mu A : X \rightarrow [0,1]$$

$\mu A(x)$ is interpreted as the degree of membership of element x in fuzzy set A for each $x \in X$.

The membership function is a graphical representation of the magnitude of participation of each input. It associates a weighting with each of the inputs that are processed, defines functional overlap between inputs, and ultimately determines an output response. The rules use the input membership values as weighting factors to determine their influence on the fuzzy output sets of the final output conclusion [22]. Once the functions are inferred, scaled, and combined, they are defuzzified into a crisp output that drives the system. There are different membership functions associated with each input and output response. Some features to note are [20]:

1. Shape: triangular is common, but bell, trapezoidal, haversine, and exponential have been used. More complex functions are possible but require greater computing overhead to implement.
2. Height or magnitude (usually normalized to 1).
3. Width (of the base of function).
4. Shouldering (locks height at maximum if an outer function, shouldered functions evaluate as 1.0 past their center).
5. Center points (center of the member function shape).
6. Overlap (N&Z, Z&P, typically about 50% of width but can be less).

Figure 7 illustrates the features of the triangular membership function, which is used in this example because of its mathematical simplicity.

Logical Operators. If we keep the fuzzy values at their extremes of 1 (completely true) and 0 (completely false), standard logical operations will hold. Now remembering that in fuzzy logic the truth of any statement is a matter of degree, the input values can be real numbers between 0 and 1. That is, resolve the statement A AND B, where A and B are limited to the range $(0,1)$, by using the function $\min(A,B)$. Using the same reasoning, we can replace the OR operation with the max function, so that A OR B becomes equivalent to $\max(A,B)$. Finally, the operation NOT A becomes equivalent to the operation $1-\mu A$.

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If-Then Rules. Fuzzy sets and fuzzy operators are the subjects and verbs of fuzzy logic [24]. If-then rule statements are used to formulate the conditional statements that comprise fuzzy logic. A single fuzzy if-then rule assumes the form if x is A, then y is B, where A and B are linguistic values defined by fuzzy sets on the ranges (universes of discourse) X and Y, respectively. An example of such a rule might be If Temperature is "High," then Fan Speed is "Fast." Note that "High" is represented as a number between 0 and 1, and so the antecedent is an interpretation that returns a single number between 0 and 1. The consequent set will later be defuzzified, assigning one value to the output. System decision mainly depends on values of the system inputs and the triggered rule base [20].

Fuzzy Expert Systems. The rules in a fuzzy expert system are usually of a form similar to the following:

if x is low and y is high then z=medium

A typical fuzzy expert system has more than one rule. The entire group of rules is collectively known as a rule-base or knowledge-base [20].

The Inference Process. With the definition of the rules and membership functions in hand, we now need to know how to apply this knowledge to specific values of the input variables to compute the values of the output variables. This process is referred to as inferencing. In a fuzzy expert system, the inference process is a combination of four subprocesses: fuzzification, inference, composition, and defuzzification. The defuzzification subprocess is optional.

Fuzzification. In the fuzzification subprocess, the membership functions defined on the input variables are applied to their actual values, to determine the degree of truth for each rule premise.

Inference. In the inference subprocess, the truth value for the premise of each rule is computed and applied to the conclusion part of each rule. This results in one fuzzy subset to be assigned to each output variable for each rule.

Two typical inference methods or inference rules are MIN and PRODUCT.

Composition. In the composition subprocess, all of the fuzzy subsets assigned to each output variable are combined together to form a single fuzzy subset for each output variable.

Two composition rules are mentioned here: MAX composition and SUM composition. SUM composition is only used when it will be followed by a defuzzification method, such as the CENTROID method, that does not have a problem with this odd case [20].

Defuzzification. Sometimes it is useful to just examine the fuzzy subsets that are the result of the composition process, but more often, this _fuzzy value_ needs to be converted to a single number—a _crisp value_. This is what the defuzzification subprocess does.

Two of the more common techniques are the CENTROID and MAXIMUM methods. In the CENTROID method, the crisp value of the output variable is computed by finding the variable value of the center of gravity of the membership function for the fuzzy value. In the MAXIMUM method, one of the variable values at which the fuzzy subset has its maximum truth value is chosen as the crisp value for the output variable [20].

Diagnostics Using Fuzzy Logic

The diagnostic process of rotating machinery through vibration analysis has several tools. The most convenient technique is the spectral analysis [3].

The amplitude spectrum or simply spectrum is a plot that represents the amplitude of each frequency component in the periodic wave. The frequency components in the spectra are usually related to the frequency of rotation when dealing with rotating machinery. The running speed component is named as 1x and the second harmonic is 2x, and so on [7].

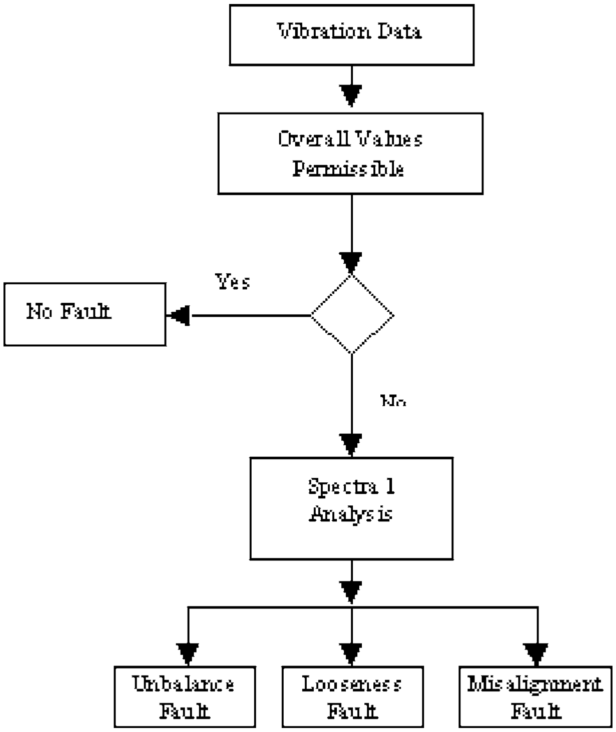

Fig. 8 Diagnosis procedure

This research is concerned with the diagnosis of three faults, namely unbalance, looseness, and misalignment. The unbalance is defined as the mass centerline is shifted from the geometrical center of the rotor. This may occur during the manufacturing as in casting process or due to wear of components. The unbalance is usually diagnosed form the spectrum by the presence of a high 1x component in the radial directions. In special cases such as in overhung rotors, the unbalance may cause high 1x vibration in the axial direction [3].

The misalignment fault is defined as the centerlines of the rotors of the driver and driven parts are not aligned together. This is a very common installation problem for rotating machinery. The misalignment is diagnosed from the spectrum by the presence of high 1x, 2x, and sometimes 3x components [3].

Looseness problems occur when the bolts that hold the bearing housing to the skid or the bolts that hold the bearing upper half to its lower half have been loosen, which is called structural looseness. In addition, when the clearances between the bearing outer race and the housing or between the bearing inner race and the shaft increased, the condition of bearing looseness occurs. The looseness can be identified from the spectrum by the presence of the 1x component with several harmonics $(2x, 3x, 4x, \ldots)$. Sometimes the $\frac{1}{2}x$ component appears with its harmonics [3].

The process of diagnosing the rotating machinery faults through vibration has several steps. In the beginning, the machine should be classified according to one of the international standards according to its characteristics (load, speed, foundation,..., etc.). The aim of this classification is to judge the machine condition, whether it is in an acceptable or an unacceptable condition. If the machine is in unacceptable condition, the analysis process should then be conducted in order to determine the machine fault(s). The following chart (Fig. 8) represents the algorithm of the diagnostic procedure used in this project.

The analysis process is usually performed by human intervention to judge the measurements. In order to perform this process

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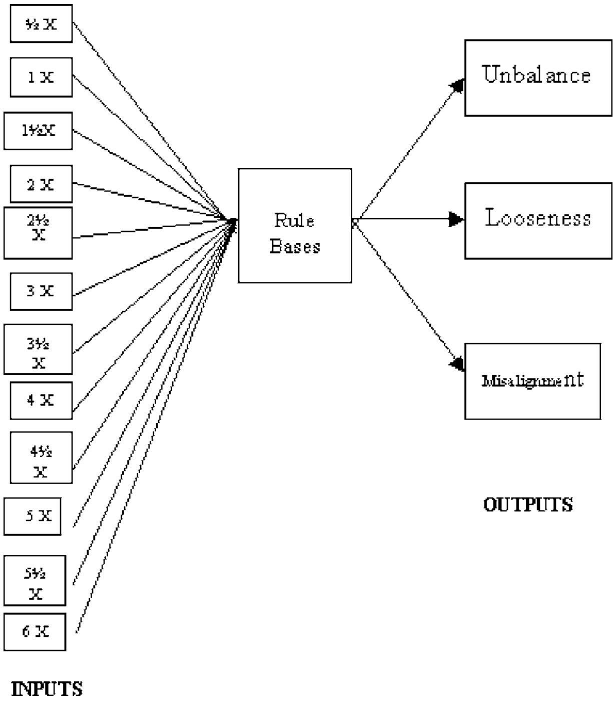

Fig. 9 Fuzzy logic system

automatically, a flexible rule set should be used, via fuzzy inference system; this is the aim of using fuzzy logic to simulate the human reasoning, because the fuzzy logic does not have a black and white decision, it has a gray scale. This is done by using the fuzzification and defuzzification process and using various types of membership functions. This flexibility is clearly found in the fuzzy logic systems. In addition, fuzzy logic has the merit of being built upon expert experience, which is the most important issue in dealing with vibration diagnosis process [25].

Table 1 Membership functions

Membership function no.	Membership function name	Left leg	Peak	Right leg
1	Very small	−0.25	0	0.25
2	Small	0	0.25	0.5
3	Medium	0.25	0.5	0.75
4	High	0.5	0.75	1
5	Very high	0.75	1	1.25

Table 3 Output results

Membership function no.	Membership function name	Value
1	No	0
2	Not sure	0.5
3.	Yes	1

Figure 9 illustrates the fuzzy logic system built for the identification of the unbalance, looseness, and misalignment faults. The system simply consists of 12 inputs representing the amplitude of the $\frac{1}{2}$x, 1x, 1$\frac{1}{2}$x, …, 6x components. These components are sufficient to diagnose the required three faults as described before. Thus this represents the low resolution configuration used for fuzzy diagnostics versus the high resolution configuration used for the neural network diagnosis [26], which relied on 400 lines of data in each spectrum.

Each input has the following properties:

Range: from 0 to 1
No. of membership functions: 5
Type of membership functions: triangular (trimf)

The membership functions are listed in Table 1. The rule bases are then applied in order to diagnose the fault. The rule base is simply an (If) statement that assigns a value of the membership function of each input and relates them by a logical operator, either (AND) or (OR) operator. Table 2 summarizes the rule bases built for the diagnosis process for the parallel configuration, which includes our expert knowledge. The output of the rule base is then produced indicating which of the three faults is found (Table 3).

Each output has the following properties:

Range: from 0 to 1
No. of membership functions: 3
Type of membership functions: constant

Note that we have used the Sugeno type inference system due to its suitability to this application [21].

Fuzzy Logic Results for Stand-Alone or Parallel Configuration

We have used the above system for fuzzy logic both as a diagnostic stand-alone system (parallel configuration), as well as in a

Table 2 Rule basis of the parallel configuration (VS: very small, S: small, M: medium, H: high, VH: very high, NO: none, N: no, Y: yes)

Inputs													Logical Operator	Outputs		
	$\frac{1}{2}$x	1x	1$\frac{1}{2}$x	2x	2$\frac{1}{2}$x	3x	3$\frac{1}{2}$x	4x	4$\frac{1}{2}$x	5x	5$\frac{1}{2}$x	6x		UN	LO	MA
	VS	VH	VS	VS	VS	VS	VS	VS	VS	VS	VS	VS	AND	Y	N	N
	S	VH	S	S	S	S	S	S	S	S	S	S	AND	Y	N	N
	VS	H	VS	VS	VS	VS	VS	VS	VS	VS	VS	VS	AND	Y	N	N
	S	H	S	S	S	S	S	S	S	S	S	S	AND	Y	N	N
	M	M	M	M	M	M	M	M	M	M	M	M	AND	N	Y	N
	H	H	H	H	H	H	H	H	H	H	H	H	AND	N	Y	N
IF	VH	VH	VH	VH	VH	VH	VH	VH	VH	VH	VH	VH	AND	N	Y	N
	NO	NO	NO	NO	NO	NO	NO	VH	NO	VH	NO	VH	OR	N	Y	N
	NO	NO	NO	NO	NO	NO	NO	H	NO	H	NO	H	OR	N	Y	N
	VS	VH	VS	VH	VS	VS	VS	VS	VS	VS	VS	VS	AND	N	N	Y
	VS	H	VS	H	VS	VS	VS	VS	VS	VS	VS	VS	AND	N	N	Y
	VS	M	VS	VH	VS	VS	VS	VS	VS	VS	VS	VS	AND	N	N	Y
	VS	S	VS	VH	VS	VS	VS	VS	VS	VS	VS	VS	AND	N	N	Y
	VS	M	VS	H	VS	VS	VS	VS	VS	VS	VS	VS	AND	N	N	Y
	VS	S	VS	H	VS	VS	VS	VS	VS	VS	VS	VS	AND	N	N	Y

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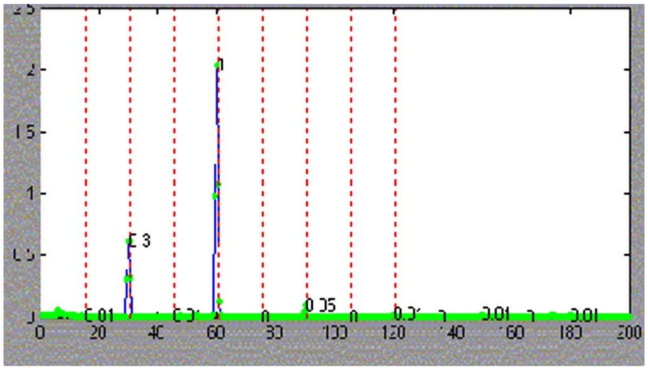

Fig. 10 Misalignment sample amplitude spectrum

series system with neural network as a first step and fuzzy logic as a second step, to provide a confidence level in the neural network diagnosis. The data used for applying the fuzzy logic system are those collected for the neural network diagnosis, as described earlier in this paper. The data collected represented the cases of no fault, unbalance fault, looseness fault, and misalignment fault, as described earlier (Fig. 10).

Applying the fuzzy logic diagnostic system rule basis of the parallel configuration to the collected data, the diagnostic results are summarized as follows.

Total cases studied: 171
No. of cases correctly identified: 168
Percentage: 98%

No fault cases studied: 99
No. of cases correctly identified: 99
Percentage: 100%
Unbalance cases studied: 18
No. of cases correctly identified: 18
Percentage: 100%
Looseness cases studied: 36
No. of cases correctly identified: 33
Percentage: 92%
Misalignment cases studied: 18
No. of cases correctly identified: 18
Percentage: 100%

The results indicate excellent performance of the built fuzzy logic system. Only 1 data file out of 171 data files introduced to the system was identified incorrectly and 2 files were not specified.

The system was able to identify the no fault, unbalance, and misalignment cases without errors, and three errors in diagnosing the looseness.

Series Configuration

The series configuration depends on developing fuzzy logic inference engine to provide a confidence level for neural networks identified cases. This technique is referred to as series configuration or series fuzzy inference (SFI). This is an application of neuro-fuzzy diagnostics [26]. Experimental data were used to test the fuzzy system and to evaluate the performance of the fuzzy inference rules.

A normalized amplitude vector is extracted from each spectrum corresponding to whole and half harmonics up to 6x. These values

Table 4 Unbalance rule basis for SFI (VS: very small, S: small, M: medium, H: high, VH: very high, L: low)

Logical operator		$\frac{1}{2}$x	1x	$1\frac{1}{2}$x	2x	$2\frac{1}{2}$x	3x	$3\frac{1}{2}$x	4x	$4\frac{1}{2}$x	5x	$5\frac{1}{2}$x	6x		Confidence Level
AND	If	VS	VH	VS	VS	VS	VS	VS	VS	VS	VS	VS	VS	Then	H
OR	If	H	-	H	H	H	H	H	H	H	H	H	H	Then	L
OR	If	V H	- -	V H	V H	V H	V H	V H	V H	V H	V H	V H	V H	Then	L
OR	If	M	-	M	M	M	M	M	M	M	M	M	M	Then	M

Table 5 Structure looseness rule basis for SFI (VS: very small, S: small, M: medium, H: high, VH: very high, L: low)

Logical operator		$\frac{1}{2}$x	1x	$1\frac{1}{2}$x	2x	$2\frac{1}{2}$x	3x	$3\frac{1}{2}$x	4x	$4\frac{1}{2}$x	5x	$5\frac{1}{2}$x	6x		Confidence Level
AND	If	⋯	VH	⋯	H	⋯	M	⋯	S	⋯	VS	⋯	VS	Then	H
AND	If	⋯	VH	⋯	VS	⋯	VS	⋯	VS	⋯	VS	⋯	VS	Then	L
AND	If	⋯	VH	⋯	S	⋯	S	⋯	S	⋯	S	⋯	S	Then	L
OR	If	M	⋯	M	⋯	M	⋯	M	⋯	M	⋯	M	⋯	Then	H
OR	If	H	⋯	H	⋯	H	⋯	H	⋯	H	⋯	H	⋯	Then	H
OR	If	VH	⋯	VH	⋯	VH	⋯	VH	⋯	VH	⋯	VH	⋯	Then	H
OR	If	⋯	⋯	⋯	⋯	⋯	⋯	⋯	VH	⋯	VH	⋯	VH	Then	H
AND	If	⋯	VH	⋯	VH	⋯	VH	⋯	VH	⋯	VH	⋯	VH	Then	H
AND	If	⋯	H	⋯	H	⋯	H	⋯	H	⋯	H	⋯	H	Then	H

Table 6 Misalignment rule basis for SFI (VS: very small, S: small, M: medium, H: high, VH: very high, L: low)

Logical operator		$\frac{1}{2}$x	1x	$1\frac{1}{2}$x	2x	$2\frac{1}{2}$x	3x	$3\frac{1}{2}$x	4x	$4\frac{1}{2}$x	5x	$5\frac{1}{2}$x	6x		Confidence Level
AND	If	⋯	VH	⋯	VH	⋯	VS	⋯	VS	⋯	VS	⋯	VS	Then	H
AND	If	⋯	VS	⋯	VH	⋯	VS	⋯	VS	⋯	VS	⋯	VS	Then	H
AND	If	⋯	VH	⋯	VS	⋯	VS	⋯	VS	⋯	VS	⋯	VS	Then	L
AND	If	⋯	VH	⋯	S	⋯	S	⋯	S	⋯	S	⋯	S	Then	L
OR	If	M	⋯	M	⋯	M	⋯	M	⋯	M	⋯	M	⋯	Then	L
OR	If	M	⋯	H	⋯	H	⋯	H	⋯	H	⋯	H	⋯	Then	L
OR	If	VH	⋯	VH	⋯	VH	⋯	VH	⋯	VH	⋯	VH	⋯	Then	L

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are utilized by the SFI to make the decision. It is worth noting that to merely test the effectiveness of the SFI, fault-planted data were used instead of neural networks identified ones. This, however, is no shortcoming since in the SFI approach neural network detection is not directly used to obtain a decision. It rather determines the fuzzy inference rule base to be applied that is selected here according to planted fault. The fuzzy system used is the Takagi-Sugeno-Kang (TSK) model with ten inputs corresponding to each element in the normalized amplitude vector [20,21]. Each input is fuzzy partitioned with triangular membership functions.

The output is limited to singletons corresponding to three confidence levels namely, low, medium, and high. The Min and Max operators were adopted to perform fuzzy conjunctive and disjunctive operations, respectively [20]. In what follows the results for identifying three different cases will be presented. Those cases are misalignment, unbalance, and structure-looseness. The confidence levels represent the results of the series configuration.

1. **Unbalance: Main characteristics**: Large 1x, no other components. Table 4 gives the unbalance rule basis using the series configuration.
2. **Structure looseness: Main characteristics**: High 1x and harmonics, sometimes half harmonics. Table 5 gives the structure looseness rule basis using the series configuration.
3. **Misalignment: Main characteristics**: High 1x and 2x, sometimes 3x. Table 6 gives the misalignment rule basis using the series configuration.

The results of applying the series configuration are as follows:

- One looseness file was incorrectly classified as misalignment (in the parallel configuration) while the actual data indicate a looseness problem. When applying the series configuration, the neural network classifies the file as looseness and the fuzzy logic system gives only 50% confidence level for the NN result.
- Two files could not be classified using the fuzzy logic system parallel configuration. When applying the series configuration the neural networks classify the files as looseness and the fuzzy logic system gives 100% confidence level for looseness in the first case and 50% confidence level for the second case.
- The remaining files were given 100% confidence level for the NN results.

Discussion and Conclusion

This effort has clearly shown the success of neural networks, stand-alone fuzzy logic, and neuro-fuzzy (SFI) systems in diagnosing the specific faults of unbalance, looseness, and misalignment.

In particular, the tools presented here along with the experimental results illustrate the possibility of applying automated diagnosis using the neural network and fuzzy logic technologies. This is in contrast to currently available diagnostic tools based on expert systems that require human intervention and provide only suggestions to possible faults. The work presented in this paper is clearly applied in an automated manner and provides a clear and definite diagnostic result.

Each of the presented methods, neural networks alone, fuzzy logic alone, or the series neuro-fuzzy application, was quite successful in its own capacity as a diagnostic tool. In particular, the success of these technologies in diagnosis in the presence of multiple faults and at different fault levels, as described in the fault planting section, and achieving such high success rates are a clear indication of the reliability of each of these diagnostic technologies.

The work here illustrated the success of the concept using neural networks as a high resolution configuration diagnostics tool for spectral data, and the use of the fuzzy logic inference system as a low resolution configuration diagnostic tool for spectral data. Moreover, the use of hybrid neuro-fuzzy diagnostic tools has been shown to be quite successful and provides a confidence index in the diagnosed faults.

Actually, the results of the paper suggest that it is possible to devise a completely automated diagnostic system based on the series neuro-fuzzy concept, or if desired it may be possible to work with two independent diagnostic tools, one based on neural networks and the other based on fuzzy logic. In this case human intervention may be required to evaluate the results from each diagnostic method.

Finally, it is intended to extend this work to other faults, to automate the diagnostics process.

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