

Automatic Machinery Fault Detection and Diagnosis Using Fuzzy Logic

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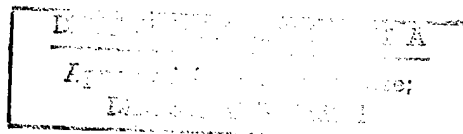
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Abstract: Vibration based machine condition monitoring (MCM) incorporates a number of machinery fault detection and diagnostic techniques. Many of the machinery fault diagnostic techniques involve automatic signal classification in order to increase accuracy and reduce errors caused by subjective human judgment. In this paper Fuzzy logic techniques have been applied to classify frequency spectra representing various rolling element bearing faults. The frequency spectra have been processed using a variety of Fuzzy set shapes. The application of basic Fuzzy logic techniques has allowed Fuzzy numbers to be generated which represent the similarity between two frequency spectra. Correct classification of different bearing fault spectra was observed when the correct combination of Fuzzy set shapes and degree of membership criterion were used. The problem of membership overlapping found in previous studies [1], where classifying individual spectrum with respect to spectra that represent true fault classes was not conclusive, has been overcome. Further work is described which will extend this technique for application with other classes of machinery using generic software.

Key Words: Fault detection, fault diagnosis, frequency spectra, Fuzzy logic, machinery faults, rolling element bearings.

Introduction: It is well recognized that optimized maintenance practices within an industrial setting require the correct blend of maintenance strategies. Condition based (reliability centered, predictive, proactive) maintenance is an important part of this blend for many compelling reasons [2]. Condition monitoring and diagnostics is also becoming more widely recognized as an integral part of automated manufacturing systems where tool performance and product quality can be used as Computer Integrated Manufacturing (CIM) input parameters. However, detection and identification of machinery faults can be difficult in systems with a high degree of complexity. This introduces uncertainties into the condition monitoring and diagnostics activities.

Recently there has been a significant amount of research effort directed towards developing and implementing useful automated machinery fault detection and diagnostic tools. Most of these tools have been based on various pattern recognition schemes, knowledge based systems (expert systems) or artificial neural network systems. The main thrust of the work has been towards developing systems that are not only objective in



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their treatment of data and presentation of results but also flexible, thereby being applicable in a wide range of situations.

Fuzzy logic has gained wide acceptance as a useful tool for blending objectivity with flexibility, particularly in the area of process control. Fuzzy logic is also proving itself to be a powerful tool when used for knowledge modeling [3] particularly when used in condition monitoring and diagnostics applications [4][5][6]. While the results reported show a degree of success, there remains a strongly subjective component to the analysis procedures. The membership functions are usually designed in a relatively subjective manner based on a preliminary inspection of the data being analyzed. The work reported on in this paper involves the use of Fuzzy logic principles in conjunction with established and accepted statistical data analysis and condition assessment standards. The procedure used is shown to be a truly objective method of categorizing vibration signals and thereby providing a means of automatically detecting and diagnosing machinery condition.

Fuzzy Logic: Fuzzy logic provides a method of reducing and explaining system complexity [3]. It deals with system uncertainties and ambiguities in a way that mimics human reasoning. It allows variables such as time, acceleration, force, distance, etc., to be represented with a degree of uncertainty. Fuzzy logic allows the membership of a variable within a group to be estimated with a prescribed degree of uncertainty. In this way, the application of Fuzzy logic to machinery fault diagnosis should allow the membership of a dynamic signal frequency spectra from an unknown source to be determined with respect to a set of spectra representing particular faults.

Fuzzy logic represents system parameters as normalized values between zero and one. The uncertainties and ambiguities associated with a system parameter can then be quantified in terms more easily interpreted by humans. For example; Is the temperature of 75°C high or low? If we know that 100°C is definitely high and 60°C is definitely low, 75°C may be considered somewhat more low than high but still not low. Fuzzy logic allows us to quantify the grey area between high and low rather than simply considering every temperature below 80°C (the mid point) to be low and every temperature above 80°C as high. So called 'crisp' boundaries are made Fuzzy but in a quantified manner. The actual degree of membership of a system parameter (temperature) in a particular group (low) is indicated by the values between zero and one inclusive. A membership of zero means that the value does not belong to the set under consideration. A membership of one would mean full representation of the set under consideration. A membership somewhere between these two limits indicates the degree of membership. The manner in which values are assigned membership is not fixed and may be established according to the preference of the person conducting the investigation.

Fuzzy sets can be represented by various shapes. They are commonly represented by S-curves, Pi curves, triangular curves and linear curves. The choice of the shape of the Fuzzy set depends on the best way to represent the data. The degree of membership is indicated on the vertical axis. In general, the membership starts at zero (no membership) and continues to one (complete membership). The domain of a set is indicated along the

horizontal axis. The fuzzy set shape defines the relationship between the domain and the membership values of a set.

The S-Curve moves from no membership at its extreme left-hand side to complete membership at its extreme right-hand side. The inflection point of the S-Curve is at the 0.5 membership point. The S-curve can also represent declining membership. It is defined by three parameters; its zero membership value (α), its complete membership value (γ) and its inflection point (β). (See Figure 1.) The domain values of an S-Curve can be determined from the following relationships [3].

$$S(x; \alpha, \beta, \gamma) = \begin{array}{ll} 0 & \rightarrow x \leq \alpha \\ 2((x-\alpha)/(\gamma-\alpha))^2 & \rightarrow \alpha \leq x \leq \beta \\ 1-2((x-\gamma)/(\gamma-\alpha))^2 & \rightarrow \beta \leq x \leq \gamma \\ 1 & \rightarrow x \geq \gamma \end{array}$$

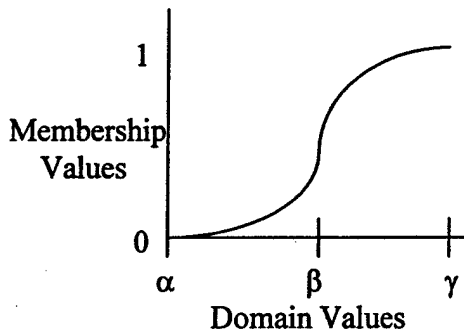


Figure 1. S-Curve

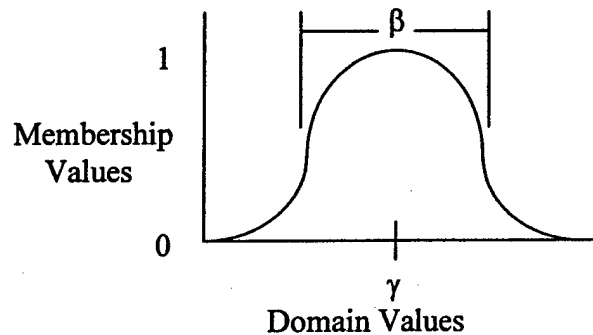


Figure 2. Pi Curve

Pi curves are the preferred and default method of presenting Fuzzy numbers where membership values have lower and upper bounds [3]. The Pi curve represents full membership at its central value. A smooth descending gradient is then observed on either side of the central value where the membership approaches zero along the domain. The parameters of the Pi curve are; the central value (γ) and the width of half of the Pi curve (β). (See Figure 2.) The domain values of the Pi curve can be determined from the following relationships where the Pi Curve is made up of ascending and descending S-Curves.

$$Pi(x; \beta, \gamma) = \begin{array}{ll} S(x; \gamma - \beta, \gamma - \beta/2, \gamma) & \rightarrow x \leq \gamma \\ 1-S(x; \gamma, \gamma+\beta/2, \gamma+\beta) & \rightarrow x > \gamma \end{array}$$

The linear Fuzzy set is the simplest Fuzzy set shape being basically a straight line. For an increasing linear Fuzzy set, no membership begins at the extreme left hand side. The line then increases linearly to the position where it represents complete membership on the right hand side. (See Figure 3.) Fuzzy sets represented by triangular curves are similar to

the Fuzzy sets represented by the Pi curve. The apex of the triangle is the central value and represents complete membership. The left and right edges of the triangle represent membership that tends toward non membership in the set. (See Figure 4.)

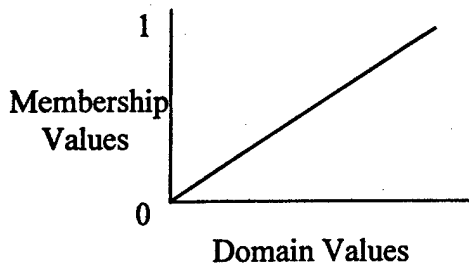


Figure 3. Linear Curve

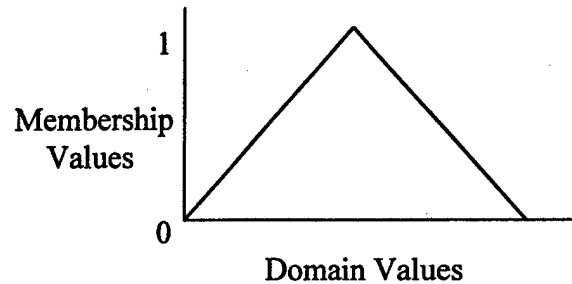


Figure 4. Triangular Curve

Signal Analysis Methodology: The aim of this work was to investigate the use of basic Fuzzy logic concepts for possible application as a machinery fault diagnostic tool. This diagnostic technique will be capable of automatic and objective machinery fault classification.

The data used in this research were frequency spectra obtained from a test rig used to conduct low speed rolling element bearing tests [7][8]. The frequency spectra obtained were representative of different bearing conditions. These bearing conditions were; No Fault (NOF), Outer Race Fault (ORF), Inner Race Fault (IRF), Rolling Element Fault (REF), Combined Outer Race and Rolling Element Faults (COM1) and Combined Outer Race, Inner Race and Rolling Element Faults (COM2). The Pi curve and the triangular curve were used to represent the frequency spectra of the various bearing conditions as members of different fault conditions. The main purpose of the investigation was to determine which Fuzzy membership curve shape worked best and to determine an objective methodology for setting the Fuzzy set membership domain limits.

Each set of frequency spectra representing different rolling element bearing faults consisted of 15 individual spectra (1 - 128 Hz). The first stage of the data analysis involved finding the mean and the standard deviation of each data set at each frequency. The average at each frequency plus or minus N times the standard deviation were the values used for the upper and lower limits of the Fuzzy membership function domains. Values of N from 1 to 10 were investigated for use with both the triangular membership functions and the Pi curve membership functions. The membership of each individual spectra was determined in relation to the average frequency spectra for a given fault type by calculating the membership at each frequency using the membership domain upper and lower limits at that frequency, adding all the membership values for each frequency together and dividing by the total number of spectral data points (128 in this case). As the upper and lower membership domain limits are changed so will the membership values for each frequency spectra.

Results: Figure 5 is an example of two typical frequency spectra derived from a dynamic vibration signal collected from a low speed rolling element bearing. (See references [7] and [8] for details of the experimental setup, data collection and signal processing.) This figure shows an outer race fault spectra and a no-fault spectra. It is clear from the figure that in this case (as well as many others) distinguishing between spectra is quite straightforward. Designing automatic diagnostic tools to work in these cases is not a problem. Difficulties arise when the differences between signals (and spectra) representing different faults are much more subtle.

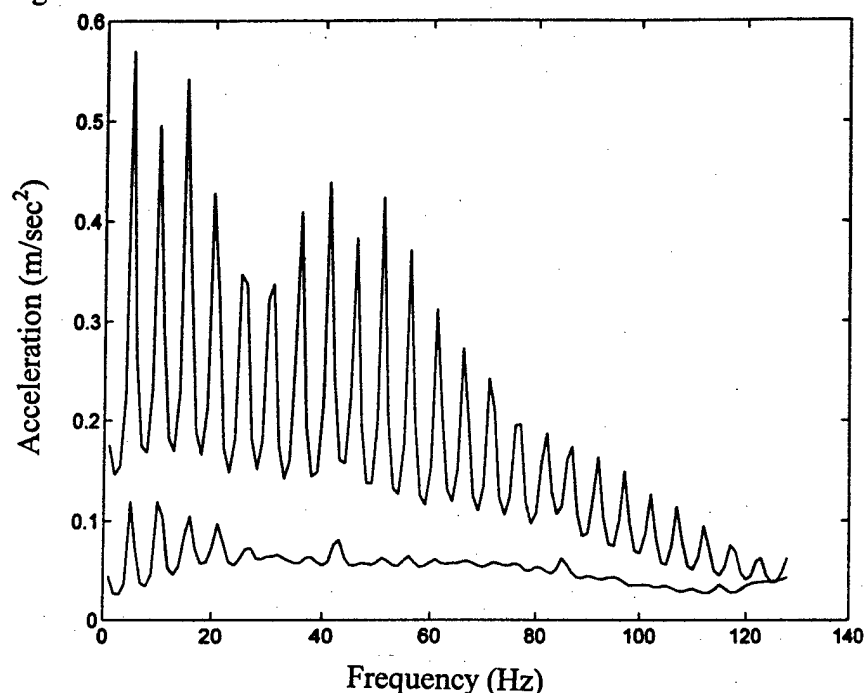


Figure 5. Outer Race Fault and No Fault Frequency Spectra.

Figure 6 is an example of two spectra representing well-developed faults of differing nature that look similar. In this case, where there is a considerable amount of uncertainty, a rigorous and finely tuned automatic diagnostic tool is required. Not only are individual samples of frequency spectra representing different faults often rather similar, but the variability within a group of spectra that represent the same fault is often significant. Figure 7 shows 15 frequency spectra that represent the same sample fault. The challenge is to provide early detection capability as well as distinction between fault types with a low risk of false alarms.

Figure 8 shows the average of the 15 different frequency spectra shown in Figure 7. Also shown are the limits that represent 2.5 standard deviations above and below the average spectra. The standard deviations were calculated at each frequency (1 to 128 in this case). This figure shows the variability within a group of frequency spectra representing one type of bearing fault condition. Similar degrees of variability exist within other fault types.

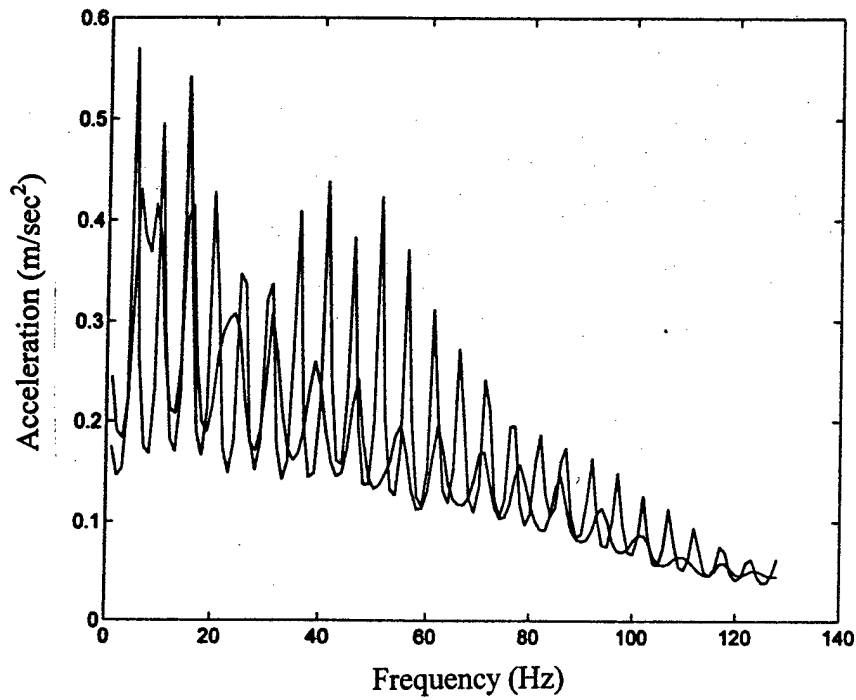
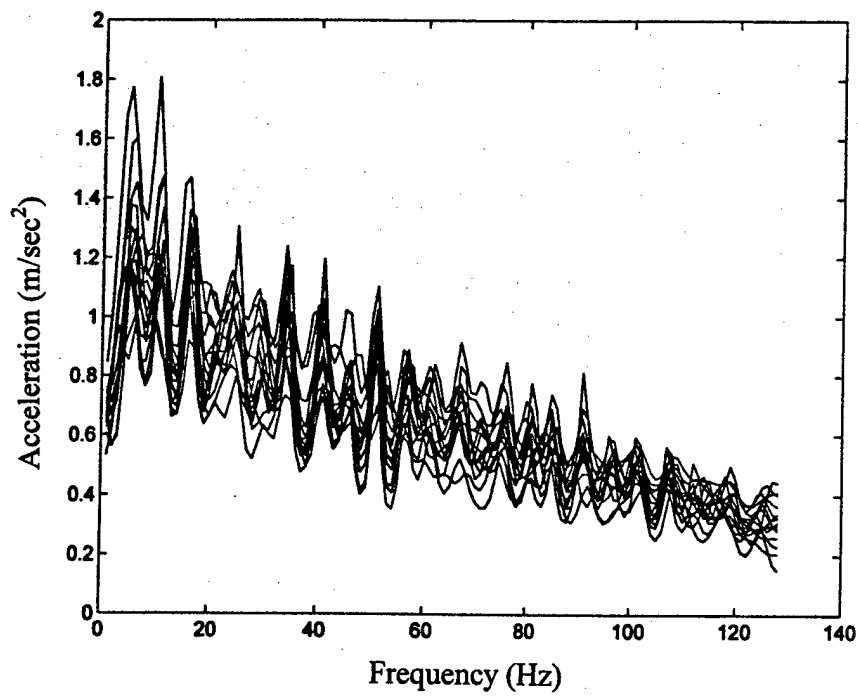


Figure 6. Outer Race Fault and Inner Race Fault Frequency Spectra.



**Figure 7. Frequency Spectra from 15 Different Vibration Signals
(Representing COM1 Type Fault)**

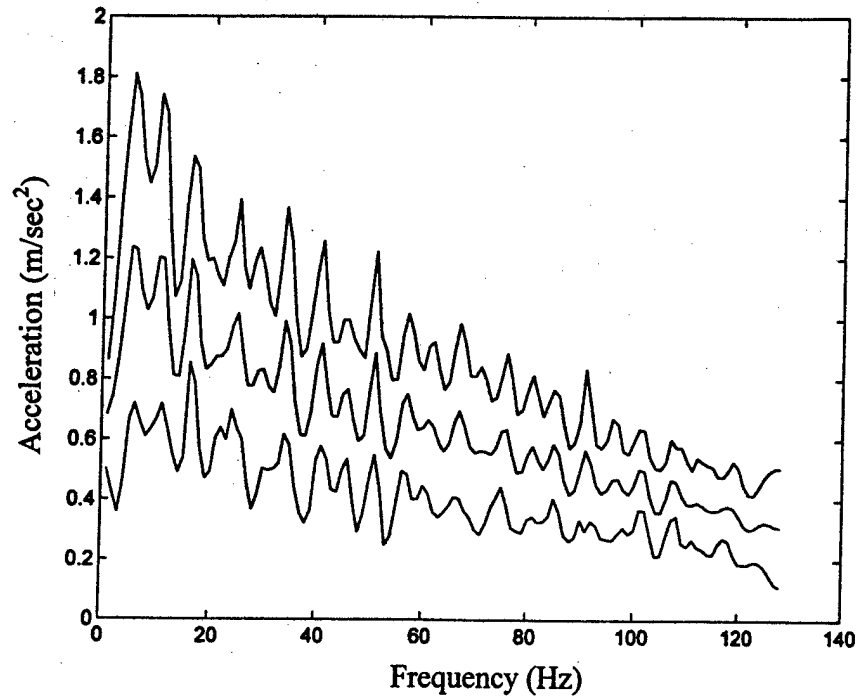


Figure 8. Average COM1 Spectra and ± 2.5 Times the Standard Deviation at each Frequency

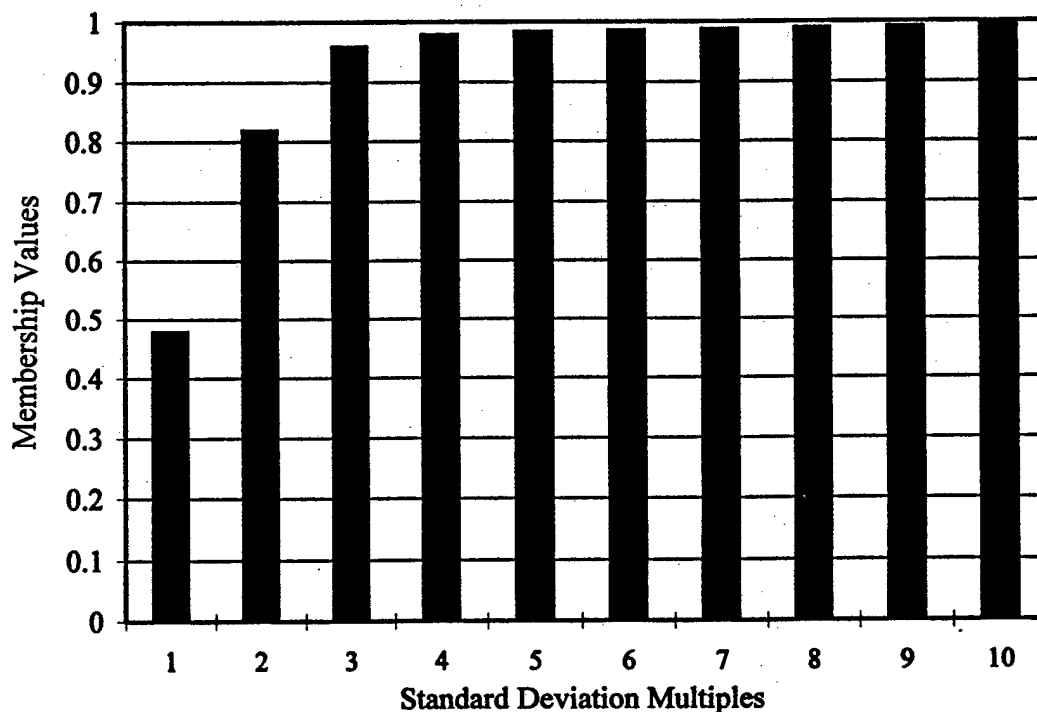
In order to optimize the Fuzzy diagnostic scheme the upper and lower Fuzzy membership function domains used were set to match different multiples of the standard deviation at each frequency. Each pair of membership domain limits were then dependent on the standard deviation of the frequency spectra at each frequency rather than being set arbitrarily.

In order to determine the best membership function shape and domain value limits a broad range of values were trialed for both the triangular membership function and the Pi-curve membership function. Table 1 shows a sample of the results from the triangular membership function trials. In this table the results are shown from a trial where a frequency spectra representing an outer race fault is compared to all the other fault types. A variety of multiples ($N = 1, 2, 3, 4, 5, 10$) of the standard deviations derived at each frequency for the given fault spectra were used as the Fuzzy membership domain limits. The same comparisons were made with all the frequency spectra. Table 1 shows a representative sample of the overall results. From these results it is evident that even when extending the upper and lower membership function domain limits to 10 times the standard deviation, a clear diagnostic trend does not develop. In fact, the distinction between a correct classification and the incorrect classifications is most clear at membership function limits of 2.0 times the standard deviation.

**Table 1: Triangular Domain Function Results
(Outer Race Fault versus Other Fault Types)**

FAULTS	N (multiples of standard deviation)					
	1	2	3	4	5	10
NOF	0.015	0.034	0.075	0.159	0.275	0.621
ORF	0.359	0.611	0.737	0.803	0.842	0.921
IRF	0.171	0.335	0.471	0.571	0.645	0.815
REF	0.132	0.275	0.407	0.518	0.601	0.788
COM1	0.0	0.0	0.003	0.007	0.017	0.058
COM2	0.0	0.0	0.002	0.005	0.008	0.039

Figure 9 is a sample bar chart of a self test classification trial conducted with all the frequency spectra correctly grouped into the different fault categories and Pi-curve membership functions. It shows that the likelihood of correct classification of any sample increases continuously with increasing membership function domain limits. An optimum efficiency is reached at four times the standard deviation. Narrower or broader limits reduce the possibility of correct classification. Using narrower limits mean fewer spectra representing a given fault type would fit that classification, while using wider limits would allow spectra representing other fault types to be classified into the class under consideration.



**Figure 9. Sample Self Test Classification Trial
(Outer Race Fault, Varying Membership Function Limits)**

Using membership function domain limits of four times the standard deviation, a cross-classification trial was conducted. Table 2 shows the results of this trial. The ability of this procedure to correctly classify frequency spectra representing different fault classes is clearly shown.

Table 2: Pi-Curve Domain Function Results

	N = 4 × Standard Deviation					
FAULTS	NOF	ORF	IRF	REF	COM1	COM2
NOF	1.0	0.204	0.224	0.459	0.001	0.0
ORF	0.088	1.0	0.499	0.551	0.031	0.0
IRF	0.102	0.560	1.0	0.682	0.013	0.0
REF	0.159	0.500	0.478	1.0	0.021	0.0
COM1	0.0	0.117	0.0	0.006	1.0	0.239
COM2	0.0	0.008	0.0	0.001	0.5218	1.0

Discussion: Linear curves, triangular curves, S-curves and Pi curves are the common membership set shapes used to represent data when using Fuzzy logic. In this study, where membership functions with upper and lower limits were required, the triangular curves and Pi-curves were used. These Fuzzy membership functions were used to classify individual frequency spectra representing different rolling element bearing fault conditions.

A trustworthy and truly objective procedure is required for the task of fault diagnosis because of the variability of different individual frequency spectra representing the same fault condition. Different frequency spectra often have similar general characteristics but may vary considerably depending on the data collection procedures followed and the machinery operating conditions during data collection. Human analysts tend to make subjective judgments that may also vary from day to day and from analyst to analyst. Figure 5 through Figure 8 shows the actual degree of variability that is common.

As described in the results section, the Fuzzy membership function upper and lower domain limits were set using a range of multiples of the standard deviation as calculated for each class of fault spectra. The optimum limit values were then sought using self test classification and cross-class classification trials. The self tests were conducted by correctly classifying a particular frequency spectra using different Fuzzy membership function domain limits. The limit that gave consistent correct classifications was considered to be the optimum.

The triangular membership domain limit results and the Pi-curve membership domain limit results both showed that as the upper and lower limits were increased the likelihood of particular frequency spectra being classified with a high degree of membership into the group where it belonged (correct classification) increased. However, the likelihood of similar spectra, belonging to other fault classes, being incorrectly classified also increased.

For the tests involving the triangular membership function it was found that a clear diagnostic trend, or optimum membership domain limit value was not reached. The

maximum distinction between correct and incorrect classification existed at membership domain limits equal to two times the standard deviation.

The tests involving the Pi-curve membership function did show a clear diagnostic trend with the optimum membership domain limit values being reached at four times the standard deviation. Narrower or broader limits acted to reduce the possibility of correct classification. Using narrower limits mean fewer spectra representing a given fault type would fit that classification, while using wider limits would allow spectra representing other fault types to be classified into the class under consideration. Table 2 shows the results of an example cross-class classification trial where the clear distinction between correct and incorrect classification is obvious. This result is possibly due to the similarity of the Pi-curve shape to the approximately Gaussian distribution that has been shown to exist in statistically stationary data collected from rotating machinery.

Concluding Comments: This work has investigated the use of basic Fuzzy logic techniques as a machinery fault diagnostic technique. The work conducted has displayed the potential of Fuzzy logic to classify frequency spectra according to the likely fault condition which they represent. Its ability to classify and identify machinery faults shows considerable potential. Using membership function domain limits that are linked to the variability of a group of spectra, that represent a particular fault type, at each frequency within the spectra allows the technique to be truly objective. This work outlines the procedure for arriving at this objective technique. The optimum limits were found manually in this study but this process could also be easily automated. Future work will focus on the task of developing generic software that will be able to import and process data from a variety of sources and representing a variety of machinery types.

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