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ORIGINAL ARTICLE

FAULT CLASSIFICATION OF CROWN WHEEL AND PINION BY AN INTELLIGENT COMBINED METHOD BASED ON DATA MINING AND FUZZY INFERENCE SYSTEM

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ABSTRACT: Vibration technique in a machine condition-monitoring program provides useful reliable information, bringing significant cost benefits to industry. The main purpose of this research is to explore the intelligent way to classify four common faults versus healthy state of differential. Vibration signal by FFT technique went to frequency domain. Then the features are extracted by using statistical feature parameters that reduced the data. The J48 algorithm as a decision tree generated fuzzy rules. The structure of the FIS classifier was then defined based on the crisp sets. Results showed that the total classification accuracy were about 90%. This work demonstrates that the combined J48-FIS model has the possible capacity for fault diagnosis of differential.

KEYWORDS: J 48 algorithm, Decision tree, Differential, Fuzzy, Fault detection, Vibration signal.

INTRODUCTION

Machine condition monitoring has long been accepted as one of the most effective and cost efficient approaches to avoid catastrophic failures of machines. It has been known for many years that the mechanical integrity of a machine can be evaluated by detailed analysis of the vibratory motion (Ahmadi and Mollazade, 2008; Peng and Kessissoglou, 2003). A faulty gear system could result in serious damage if defects occur to one of the gears during operation condition. Early detection of the defects, therefore, is crucial to prevent the system from malfunction that could cause damage or entire system halt. Diagnosing a gear system by examining the vibration signals is the most commonly used method for detecting gear failures. Vibration signals carry information about exciting forces and the structural path through which they propagate to vibration transducers. The conventional methods for processing measured data contain the frequency domain technique, time domain technique, and time–frequency domain technique. These methods have been widely employed to detect gear failures. The use of vibration analysis for gear fault diagnosis and monitoring has been widely investigated and its application in industry is well established (Cameron and Stuckey, 1994; Gadd and Mitchell, 1984). Artificial neural networks (ANNs) and fuzzy logic have been applied to automated detection and diagnosis of rectitude of machine. They mainly magnify the safety of fault detection and diagnosis systems (Nejjari and Benbouzid, 2000; Chow, 1997). Azadeh *et al.*, (2010) were used A fuzzy inference system for pump failure diagnosis by vibration signals. Wang and Hu were used Vibration signals for fault diagnosis of pump using fuzzy technique. In this research, fuzzy logic principle is used as a fault diagnostic technique to describe the uncertain and ambiguous relationship between different fault symptoms and the events, analyze the fuzzy information existing in the different phases of fault diagnosis and condition monitoring of the pumps, and classify frequency spectra representing various pump faults (Wang and Hu, 2006). Twiddle and Jones, (2011) were used Fuzzy model for condition monitoring and fault diagnosis of a diesel engine cooling system. In this research differential of Peugeot-Roa, that is one of high production automobile in Iran, was used as case study for condition monitoring of differential.

MATERIALS AND METHODS

The experimental setup with data acquisition, sensor and other parts are shown in Figure 1. A constant speed of differential provide by 3hp electromotor at the 800 RPM. The differential shaft is attached to the shaft of the motor through a coupling. In the present study, three pinions and three crown wheels were used. One was a new Pinions and crown wheels and was assumed to be

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free from defects. In the other two pinions and crown wheels, defects were created by removing a small portion of metal through a machining process. The selected area on the top of the differential for mounting the sensor is made flat and smooth to ensure effective coupling between the sensor and the differential. With the sensor mounted on top of the differential vibrations signals are obtained for various conditions. The differential conditions to be considered were healthy, broken crown wheel, worn crown wheel, broken pinion and worn pinion. The sensor used is a piezoelectric accelerometer (VMI 102). The accelerometer is connected to the signal conditioning unit (Easy-Viber FFT analyzer). The vibration signal in digital form is fed to the computer through a USB port. The software Spectra Pro-4, which accompanies the signal conditioning unit, is used for recording the signals directly in the computer's secondary memory. The signal is then read from the memory and processed to extract different features.

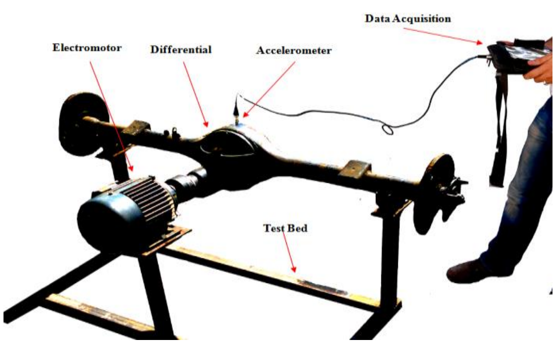

Figure 1: The experimental set-up.

The vibration signals acquired for various experimental conditions form the differential using FFT are shown in Figure 2.

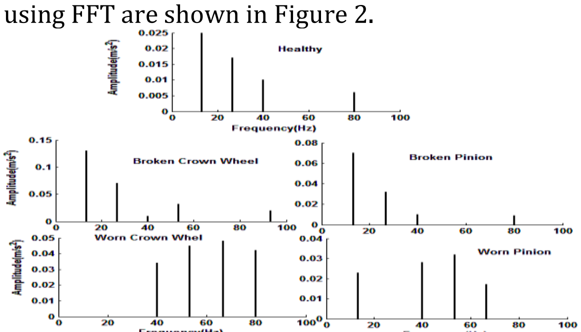

Figure 2: Vibration signal for different conditions of crown wheel and pinion.

2.1. Feature Extraction

Statistical analysis of vibration signals yields different primary and secondary Parameters. Research work reported (James and Wu, 1989) use these in combinations to elicit information regarding bearing faults. Such procedures use allied logic often based on physical Considerations. For more information about used features, see (Saravanan *et al.*, 2009). All the above mentioned statistical features were extracted for the vibration signals obtained for various conditions and fed as an input to J48 algorithm for selecting the best features which classify the different fault conditions.

2.2. Using J 48 Algorithm In The Present Work

A standard tree induced with c5.0 (or possibly id3 or c4.5) consists of a number of branches, one root, a number of nodes and a number of leaves. One branch is a chain of nodes from root to a leaf; and each node involves one attribute. A decision tree is a tree based knowledge representation methodology used to represent classification rules. In this research, j48 algorithm (a weka implementation of c4.5 algorithm) is a widely used one to construct decision trees (Saravanan *et al.*, 2009). The decision tree various statistical parameters are selected for the various conditions of the differential. The values appearing between various nodes in the decision tree are used for generating the fuzzy rules to classify the various conditions of the differential under study. The data sets of the features for each condition have 45 samples. In each operating condition, two-thirds of samples are employed for the training process and the other samples for testing. The outputs of the J48 algorithm are presented in Figure 3.

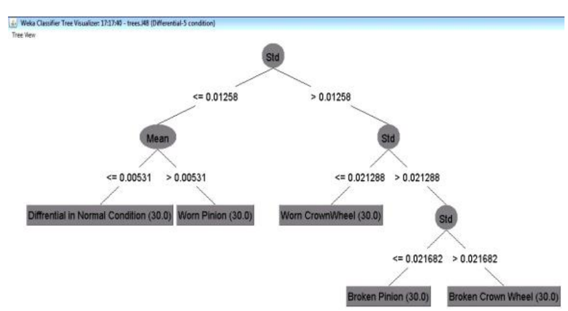

Figure 3: The decision tree of J48 algorithm.

The classification results based on decision trees are calculated using a 10-fold cross-validation evaluation where the data set to be evaluated is randomly partitioned so that in each condition 30 samples are used for training. The process is iterated with different random partitions and the results are averaged. Obtained confusion matrices from the decision trees are shown in Figure 4. In a confusion matrix, each cell contains the number of samples that was classified corresponding to actual algorithm outputs. The diagonal elements in the confusion matrix show the number of correctly classified instances. Results show that the accuracy of decision trees is about 97.30%.

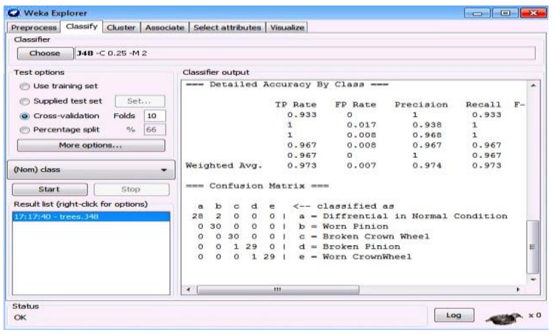

Figure 4: Confusion matrices of decision trees for differential.

2.3. Fuzzy Logic (Classifier)

Fuzzy logic provides a precise approach for dealing with uncertainty. Fuzzy inference is a method that interprets the values in the input vector and, based on some set of rules, assigns values to the output vector. The point of fuzzy logic is to map an input space to an output space, and the primary mechanism for doing this is a list of 'if-then' statements called rules. Rules are the inputs for building a fuzzy inference engine. All rules are evaluated in parallel, and the order of the rules is unimportant (Saravanan *et al.*, 2009). A membership function (MF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. Observing the values of the feature, based on which the branches of the decision tree are created for different conditions of the differential, the membership functions for the corresponding features are defined. Rules are defined such as IF (condition) THEN (result). After defining membership functions and building the if-then rules by J48 algorithm, then the fuzzy inference engine was constructed in fuzzy toolbox of Matlab^{R2011b} (Hahn and Valentine, 2007). Artificial neural network and support vector machine are used to generate rule for classification problems (Andrews *et al.*, 1995; Moosavian *et al.*, 2012). In this study, decision tree is used for that purpose. Decision tree shows the relation between features and the condition of the differential. Tracing a branch from the root node leads to a condition of the differential (Figure 3) and decoding the information available in a branch in the form of 'if-then' statement gives the rules for classification using fuzzy for various conditions of the differential. Hence the usefulness of the decision tree in forming the rules for fuzzy classification is established.

From Figure 3 we can see that standard deviation and mean play a decisive role in classifying the various differential faults. In the present study, trapezoidal membership function is used. This output of the decision tree is used to design the membership function for fuzzy classifier as shown in Figure 5. A membership function (MF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. There are five possible outcomes from a fuzzy classifier, namely: differential in normal condition, broken crown wheel, broken pinion, worn crown wheel and worn pinion. Hence, five membership functions are defined with equal range for the output (Figure 6).

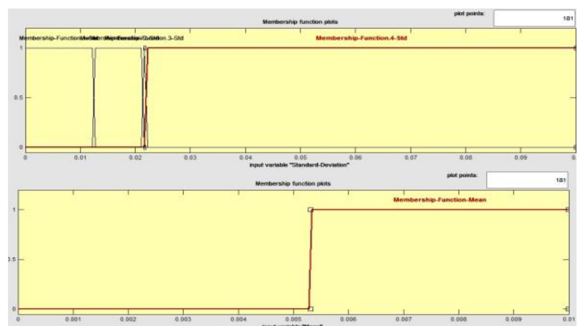

Figure 5: Two samples of defined membership functions for this work.

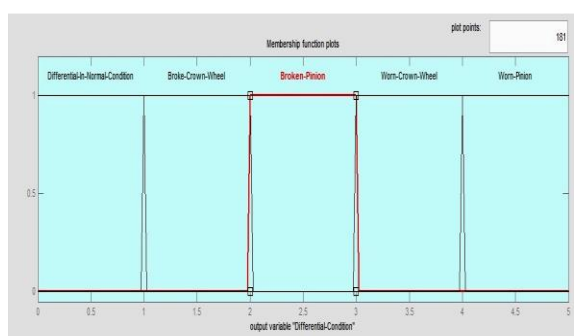

Figure 6: Membership function for output.

2.4. Fuzzy Rules

Using Figure 3, fuzzy rules were designed with if-then statements. All rules are evaluated in parallel, and the order of the rules is unimportant.

Rules designed for differential:

1. If (Mean is not Membership-Function-Mean) and (Standard-Deviation is Membership-Function.1-Std) then (Differential-Condition is Differential-In-Normal-Condition) (1)
2. If (Standard-Deviation is Membership-Function.4-Std) then (Differential-Condition is Broke-Crown-Wheel) (1)
3. If (Standard-Deviation is Membership-Function.3-Std) then (Differential-Condition is Broken-Pinion) (1)
4. If (Standard-Deviation is Membership-Function.2-Std) then (Differential-Condition is Worn-Crown-Wheel) (1)
5. If (Mean is Membership-Function-Mean) and (Standard-Deviation is Membership-Function.1-Std) then (Differential-Condition is Worn-Pinion) (1)

Figure 7, shows the application of the rules designed. Here each row corresponds to each rule as discussed in this section. The first two blocks in rows represent the MFs of mean and standard deviation, respectively. The third block corresponds to the MFs for output as shown in Figure 6. With the help of sample inputs for mean as 0.0034 and standard deviation as 0.043, which satisfies the second rule completely and the corresponding output condition is broken crown wheel, which is shown in the output block of the third row in the rule viewer shown in Figure 7.

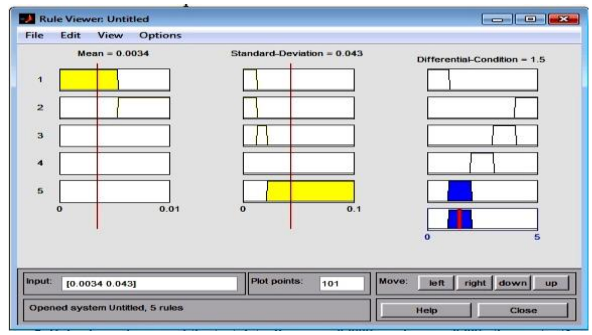

Figure 7: Rule viewer for one of the test data. If mean = 0.0034, standard deviation = 0.043, then output1 = 1.5.

The confusion matrix for each condition is given in Table 1. Results show that the total classification accuracy was 89.33%.

Table 1: Confusion matrices of decision trees for differential

Condition / Predicted	Differential in normal condition	Broken crown wheel	Worn crown wheel	Broken pinion	Worn pinion
Differential in normal condition	13	0	0	2	0
Broken crown wheel	0	14	0	0	1
Worn crown wheel	0	0	15	0	0
Broken pinion	2	1	0	12	0
Worn pinion	1	0	0	1	13

CONCLUSION

Fault diagnosis of deferential is one of the core research areas in the field of condition monitoring of rotating machines. The work conducted, proposing the method of classification the likely fault conditions which are represent in rotating machinery. From the study carried out and presented in this paper, the diagnosis technique based on the fuzzy logic principle is found to be practical for the condition recognition of the differential. Also this work brings out the potential of decision trees to generate the rules automatically from the feature set which proves to be a great asset in generating fuzzy rules. This work has outlined the procedure of fuzzy diagnosis technique by using the characteristic variables which represent a particular running condition of the differential to determine the fuzzy membership function.

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