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Online Fault Monitoring System using Multi Agent Software

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Abstract

It is well known that from global developments in the field of production technology that further rationalization and automation of manufacturing techniques must continue which seems that the advances will be towards machine tools which will to a large extent be capable of looking after them.

The machines with such capabilities have the prerequisite for a full economic exploitation and thus satisfactory amortization factors of their high investment cost. The realization of such machines, however, will remain an utopian dream until it becomes possible to monitor completely the sometimes complex mechanisms of the machine, peripheral devices and control with respect to their functioning, to diagnose the cause of failures and finally to perhaps automatically eliminate them.

Introduction

Condition monitoring of machinery has increased in importance as more engineering processes are automated and the manpower required to operate and supervise plants is reduced. The monitoring of the condition of machinery can significantly reduce the cost of maintenance. Firstly, it can allow an early detection of potential catastrophic fault, which could be extremely expensive to repair. Secondly, it allows the implementation of conditions based maintenance rather than periodic or failure based maintenance. In these cases, significant savings can be made by delaying schedule maintenance until convenient or necessary. Although there are numerous efficient methods for modeling of mechanical systems, they all suffer the disadvantage that they are only valid for a particular machine. Changes within the design or the operational mode of the machine normally require a manual adaptation. Using Neural Networks to model technical systems eliminates this major disadvantage. The basis for a successful model is an adequate knowledge base on which the network is "trained". Without prior knowledge of the machines systematic behavior or its history, training of a neural Network is not possible. Therefore, it is a pre-requisite that the knowledge base contains a complete behavior of the machine covering the respective operational modes whereby, not all rather the most important modes are required. Neural networks have a proven ability in the area of nonlinear pattern classification. After being trained, they contain expert knowledge and can correctly identify the different causes of vibration. The capacity of artificial neural networks to mimic and automate human expertise is what makes them ideally suited for handling nonlinear systems.

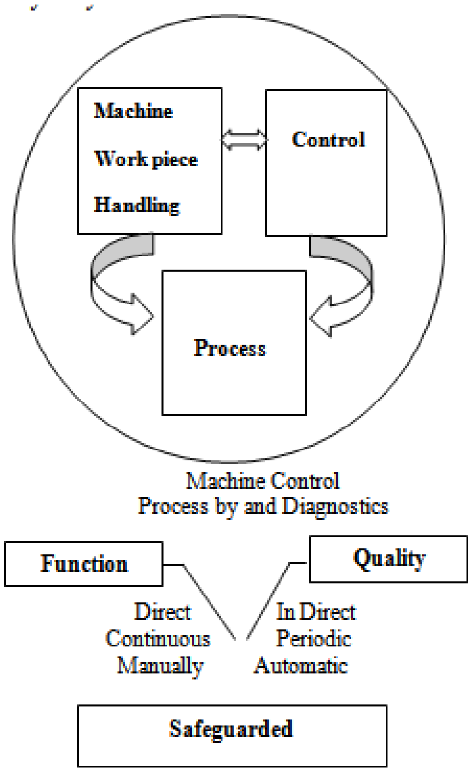
Acoustic Emission

The interest for applications of acoustic emission for condition monitoring in rotating machinery has grown significantly over the last decade. In an area where vibration monitoring dominates for several decades successfully in many industrial applications, acoustic emission offers some attractive advantages over vibrations. First of all, as AE is anon-directional technique, one AE sensor is sufficient to perform the task in contrast to vibration monitoring which may require information from three axes. Since AE is produced at microscopic level it is highly sensitive and offers opportunities for identifying defects at an earlier stage when compared to other condition monitoring techniques. As AE mainly detects high-frequency elastic waves, it is not affected by structural resonances and typical mechanical background noise (under 20 kHz). Sources of AE in rotating machinery include asperities contact, cyclic fatigue, friction, turbulence, material loss, cavitations, leakage, etc. For instance, during the interaction of the surface asperities the oil film that covers the teeth locally increases its pressure generating a varying pressure profile. This transient pressure profile generates elastic waves that propagate on the surface of the material as Rayleigh waves and the displacement of these waves is measured with an AE sensor. In addition to this continuous type AE from the asperities contact, any crack initiation and pitting type of damage can also give rise to significant AE that is captured by the data acquisition board.

Methodology

Machine condition monitoring is gaining importance in industry because of the need to increase reliability and to decrease the possibility of production loss due to machine breakdown.

Using the diagnostic principles as set out in the figure it becomes possible to ensure that the function and quality of components of the production process are maintained at a satisfactory standard



The use of vibration and acoustic emission (AE) signals is quite common in the field of condition monitoring of rotating machinery. By comparing the signals of a machine running in normal and faulty conditions, detection of faults like mass unbalance, rotor rub, shaft misalignment, gear failures, and bearing defects is possible. These signals can also be used to detect the incipient failures of the machine components, through the online monitoring system, reducing the possibility of catastrophic damage and the downtime. Although often the visual inspection of the frequency domain features of the measured signals is adequate to identify the faults, there is a need for a reliable, fast, and automated procedure of diagnostics. Artificial neural networks (ANNs) have potential applications in automated detection and diagnosis of machine conditions. Multilayer perceptrons (MLPs) and radial basis functions (RBFs) are the most commonly used ANNs though interest in probabilistic neural networks (PNNs) is also increasing recently. The main difference among these methods lies in the ways of partitioning the data into different classes. The applications of ANNs are mainly in the areas of machine learning, computer vision, and pattern recognition because of their high accuracy and good generalization capability Bearing Fault Detection Using ANN and Genetic Algorithm, a procedure was presented for condition monitoring of rolling element bearings comparing the performance of the classifiers MLPs and RBFs with all calculated signal features and fixed parameters for the classifiers.

In this, vibration signals were acquired under different operating speeds and bearing conditions. The statistical features of the signals, both original and with some preprocessing like differentiation and integration, high- and low pass filtering, and spectral data of the signals, were used for classification of bearing conditions. However, there is a need to make the classification process faster and accurate using the minimum number of features which primarily characterize the system conditions with optimized structure or parameters of ANNs. Genetic algorithms (GAs) were used for automatic feature selection in machine condition monitoring. In a GA-based approach was introduced for selection of input features and number of neurons in the hidden layer. The features were extracted from the entire signal under each condition and operating speed. In some preliminary results of MLPs and GAs were presented for fault detection of gears using only the time domain features of vibration signals. In this approach, the features were extracted from finite segments of two signals: one with normal condition and the other with defective gears. In the present work, the procedure is extended to the diagnosis of bearing condition using vibration signals through ANN classifiers. Comparisons are made between the performance of the different types of ANNs, both with and without automatic selection of input features and classifier parameters. The classifier parameters are the number of hidden layer neurons in MLPs and the width of the radial basis function in RBFs and PNNs. Figure 1 shows a flow diagram of the proposed procedure.

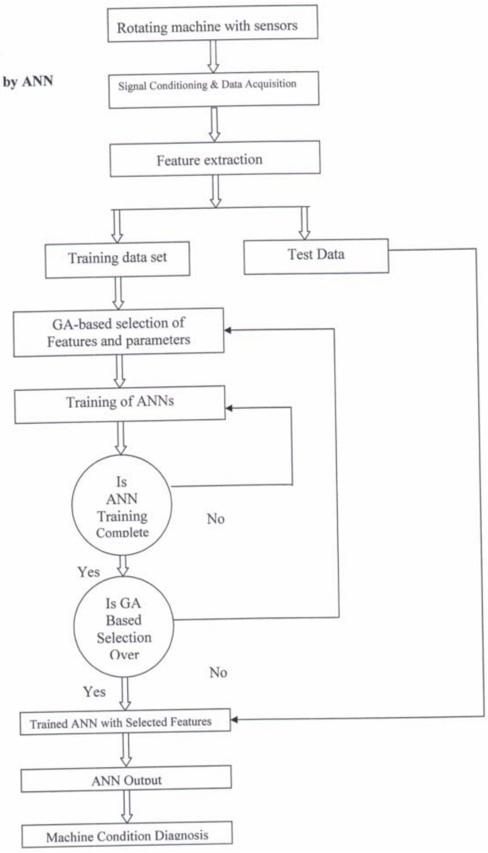
The selection of input features and the classifier parameters are optimized using a GA-based approach. These features, namely, mean, root mean square, variance, skew ness, kurtosis, and normalized higher-order central moments are used to distinguish between normal and defective bearings. The roles of different vibration signals are investigated. The results show the effectiveness of the extracted features from the acquired and preprocessed signals in diagnosis of the machine condition. The procedure is illustrated using the vibration data of an experimental setup with normal and defective one.

Experimental Procedures

In our experimental procedure let us deal with the mechanical component of a bearing as illustrated in the figure 2 below

Figure - I

Training by ANN



Rolling Element Bearing

The basic purpose of a machine bearing is to provide a near frictionless environment and to support and guide a rotating shaft. Rolling element bearings, regardless of type (ball, cylindrical, spherical, tapered, or needle) consist of an inner and an outer race separated by the rolling elements, which are usually held in a cage as shown in Figure

3. Mechanical flaws may develop on any of these components. Using the basic geometry of a bearing, the fundamental frequencies generated by these flaws can be determined.

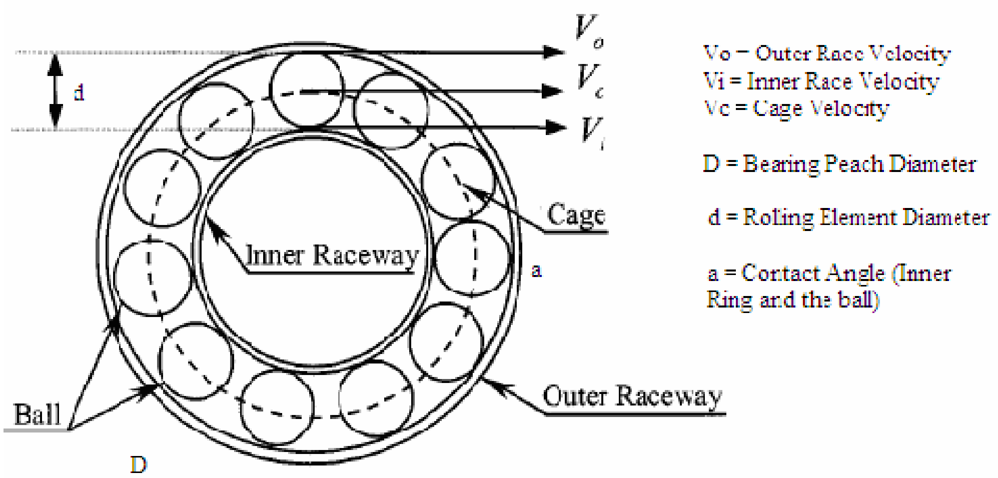
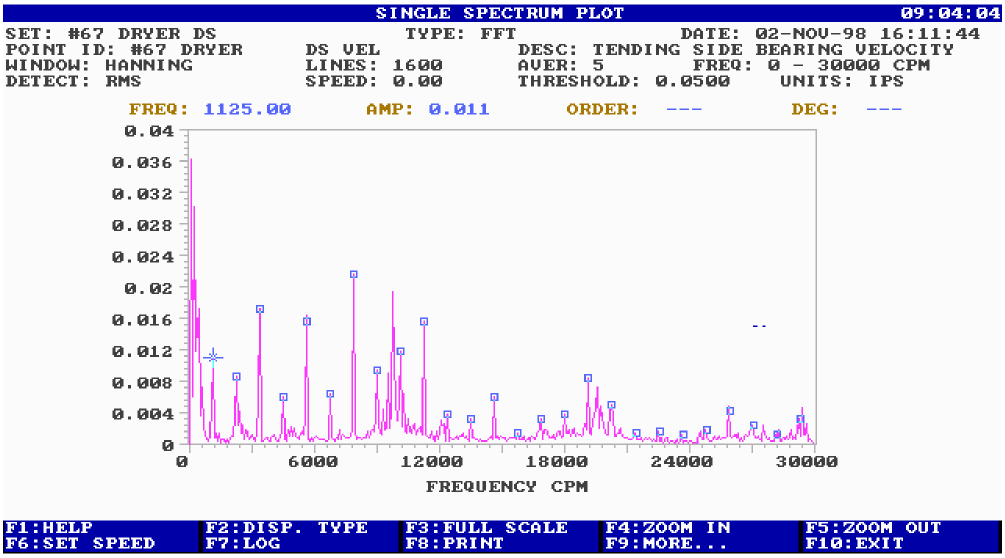


Figure 3: Basic rolling element bearing geometry

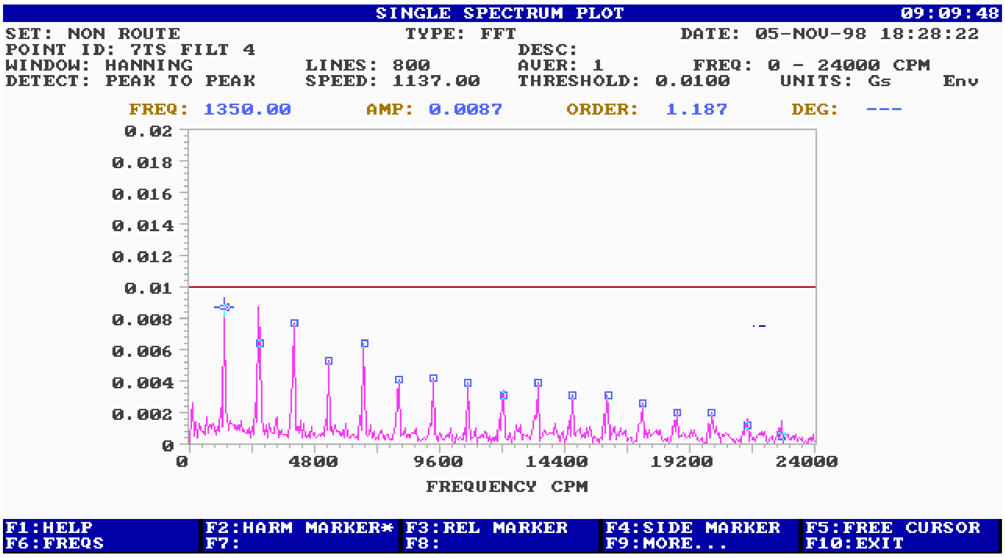
All rolling element bearings have one thing in common: all parts must be in physical metal to metal contact at all times. Installation instructions specify the amount of bearing pre-load to maintain the component contact. Two general bearing styles are utilized at this time: the journal bearing and the rolling element bearing. For lower horsepower and lighter loaded machines, the rolling element bearing is a popular choice . Some of the reasons why the rolling element bearings are used are: low starting friction, low operating friction, ability to support loads at low (even zero) speed, lower sensitivity to lubrication and the ability to support both radial and axial loads in the same bearing. By themselves, rolling element bearings have very little damping, so whenever a machine with rolling element bearings traverses a balance resonance, large vibration can result. Also, compared to fluid film bearings which generally have a long life, rolling element bearings have a limited fatigue life due to the repeated stresses involved in their normal use. Rolling element bearings have some unique concerns not found in journal bearings. A rolling element bearing will always force a vibration node at its location. Because of the metal to metal contact, this bearing will provide very little vibration damping. Although these bearings are a very precisely machined part they have a limited lifetime. Each component of the bearing will generate specific frequencies as defects initiate and become more prevalent.

The spectrum shows harmonics of this bearings outer race defect frequency at 1125 RPM. These frequencies were produced by a defect 8 inches long and 1 ½ inches wide.

The spectrum plot as shown in the figure 4 & figure 5 below gives the detail picture of frequency domains



Spectrum plot - figure 5



These spectrum plots are designed based on the frequency obtained from the acoustic emission signal, which is compared with the threshold frequency. If the current frequency is above the threshold it is found the current component is being defective and it should be replaced immediately.

Neural Network

We all know that the neural network is a Information processing system, which works in similar to biological system of a brain. Here we are implementing the neural network to predict the fault of such mechanism by a genetic algorithm.

Genetic Algorithm

The GA is a stochastic global search method that mimics the metaphor of natural biological evolution. GAs operate on a population of potential solutions applying the principle of survival of the fittest to produce (hopefully) better approximations to a solution. At each generation, a new set of approximations is created by the process of selecting individuals according to their level of fitness in the problem domain and breeding them together using operators borrowed from natural genetics. . This process leads to the evolution of populations of individuals that are better suited to their environment than the individuals that they were created from, just as in natural adaptation].One may think that generating populations from only two parents may result in losing the best chromosome from the last population. This is true, and so elitism is often used. This means, that at least one of a generation's best solution is copied without changes to a new population, so the best solution can survive to the succeeding generation.

Working Model of Genetic Algorithm

1. **[Start]** Generate a random population of *n* chromosomes (suitable solutions for the problem)
2. **[Fitness]** Evaluate the fitness *f(x)* of each chromosome *x* in the population
3. **[New population]** Create a new population by repeating the following steps until the new population is complete
4. **[Selection]** Select two parent chromosomes from a population according to their fitness (the better their fitness, the bigger their chance to be selected)
5. **[Crossover]** with a crossover probability cross over the parents to form new offspring (children). If no crossover was performed, offspring is the exact copy of parents.
6. **[Mutation]** with a mutation probability mutate new offspring at each locus (position in chromosome).
7. **[Accepting]** Place new offspring in the new population
8. **[Replace]** Use new generated population for a further run of the algorithm
9. **[Test]** If the end condition is satisfied, **stop**, and return the best solution in the current population
10. **[Loop]** Go to step **2**

The model structure of diagnosis system

This system includes a main interface and four function modules as data acquisition and preprocessing, signal analysis, fault diagnosis and database management system.

The main functions of data acquisition and preprocessing are to classify and dispose vibration signals .After acquiring the value of fault symptoms, this module sets up a database, which will be diagnosed.

The next step is signal analysis where the vibration signals are analyzed to calculate the amplitude and phase on every frequency. Through this signal analysis we can plot a graph illustrating the frequency domains under different amplitude.

The fault diagnosis setup compares the current frequency with the threshold frequency and displaces the result.

The function of database management module is to set up a diagnosis bank. Here the diagnosis strategy will be displaced to the user.

The utilization of Multi agent (MAS)

Multi-Agent Opportunism: The ability of agents operating in a MAS to assist one another by recognizing potential opportunities for each other's goals, and responding by taking some action and/or notifying the appropriate agent or agents

Approach

Augment existing approaches to single-agent opportunism and MAS coordination mechanisms with sufficient knowledge-sharing capabilities to allow agents to recognize and respond to opportunities for one another.

Benefits

Allow the MAS to better adapt to its changing environment by exploiting unexpected events Improve in the overall performance of the MAS by allowing agent to complete suspended goals/tasks early (or at all) Ensure agents obtain critical information in a timely fashion (i.e. "Precision-Guided Information")

Conclusion

The use of testing the vibrating signal as an input to an Artificial Neural Network has proven successful in the diagnosis of mechanical faults in rotating machinery. It is capable of capturing and revealing, through changes in energy level, minute changes within characteristic frequencies resulting from various levels of damage. These captured changes are sufficient to be interpreted by an Artificial Neural Network utilizing the supervised learning genetic algorithm. Further expansion of this technique will enable complete system monitoring, resulting in decreased equipment failure, decreased equipment down time, and a decrease in equipment operating costs.

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