A monitoring concept for pumps with variable speed

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ABSTRACT: In this paper we discuss a new approach for monitoring a group of recirculation pumps in a German boiled water reactor. The special problem in this application is the dependence of almost all diagnosis parameters on the pump rotating speed. This concept uses elements of the fuzzy logic for accurately analyzing machine behavior and diagnosing machine malfunctions without a crisp comparison with limit values and is able to process learning samples if only one state class is specified.

1 INTRODUCTION

The utilisation of vibrational signals has proved to be a suitable method of diagnosis for many applications in machine monitoring. Special problems of automatic classification, that is, the assignment of a vibrational pattern to a machine condition, occur especially in the case of machines with variable rotational speed, and in the presence of further severely fluctuating process parameters which immediately affect the vibrational behaviour. For this reason, the monitoring system described here utilises a fuzzy classification algorithm, which appears to be suited for providing a reliable diagnostic result despite these dependencies, by the selection of an appropriate membership function, as indicated by experience to date. A similar vibration monitoring system has been applied in diverse fields of the chemical industry, such as the surveillance of continuously operating centrifuges, and has allowed successful detection of various defects even during the incipient stage and thus avoided possible consequential damage.

In the operation of nuclear power stations, safety aspects impose stringent requirements on the reliability of process control in many areas; as a rule, this can be achieved only by means of automatic monitoring of the machines relevant to the process.

As an approach for monitoring the machine condition, the diagnostic system described here involves the measurement of machine vibration in the frequency range up to 50 kHz, as well as other process variables, such as pressure, temperature, etc. On this basis, inadmissible rotor deflections, surface caking, crack initiation in turbine blades, instabilities, and damage to journal and roller bearings can be reliably detected.
A monitoring system of this kind was initially developed by the authors for machines with constant rotational speed and has been successfully tested in monitoring of continuously operating centrifuges for several years. In order to suppress the usually high interference level, which frequently results in considerable impairment of the signal quality, as well as the accompanying severe fluctuation of the process parameters, a fuzzy classification algorithm is applied for the purpose. Moreover, a fuzzy approach of this kind is considerably better suited for indicating changes in state, such as a damage process, than would be possible with sharp limiting value specifications.

In the present paper the experience hitherto gained with this monitoring system in industrial applications is first briefly outlined; on this basis, a necessary modification of the classifier for rotor systems with variable rotational speed is then described. We discuss a new approach for monitoring a group of internal forced circulation pumps in a German boiled-water reactor. The special problem in this application is the dependence of almost all diagnosis parameters on the pump rotating speed, because this kind of pump shows a variable speed from 500 min$^{-1}$ to 2000 min$^{-1}$.

2 FUZZY CLASSIFICATION ALGORITHM

For the problem of machine monitoring a mathematically describable relationship between the cause of damage and vibration signal is available only in some cases. The mathematical formulation of fuzzy sets is an essential for designing a classifier of this kind. The basic function of the classifier is the assignment of an unknown state to one of the $N$ decision classes, $\Omega_c$. If the number of classes present is indexed by $n = 1, \ldots, N$, and the features of the feature vectors by $j = 1, \ldots, J$, we can introduced with the average value vector, $\bar{r}_c$, of the learning sample $\bar{x}_n$ for the class $\Omega_c$ a membership function:

$$
\mu_c(\bar{x}) = \frac{1}{1 + a \cdot \sum_{j=1}^{J} \frac{1}{\lambda_{c,j}} \cdot [(\bar{x} - \bar{r}_c)^T \cdot \bar{c}_{c,j}]^2}
$$

(1)

Distances in different coordinate axes can be thereby weighted individually. Marginal random sample elements can be appraised similarly even for different Euclidean distances. The eigenvectors, $\bar{c}_k$, of a rotated coordinate system can be calculated as an estimated value of the class-specific covariance matrix,

$$
\bar{c}_c = \frac{1}{N - 1} \sum_{n=1}^{N} (\bar{x} - \bar{r}_c)^T (\bar{x} - \bar{r}_c).
$$

(2)

A lot of positive experiences with this classifier show, that for monitoring of rotating machinery with constant speed Eq. 1 is suited for an adequate matching of the membership function to the learning sample. This is achieved by means of the free parameters after completion of the learning phase.
3 ADAPTED CLASSIFICATION ALGORITHM

The situation of design a vibration monitoring system is especially serious in the case of automatic diagnosis for machines with variable rotational speed, where the vibrational behaviour and the scatter of the features derived from the vibrational signal can vary over the entire rotational speed range. If, in addition, resonant frequencies with local excess amplitudes occur in the range being monitored, the resulting random sample distributions may be highly complex. In figure 2, the qualitative distribution is plotted for 700 measurements of the diagnostic variable, shaft rotational speed vibration amplitude, for a recirculation pump with journal bearings in nonsteady-state operation. This kind of pumps have a variable speed from 500 min$^{-1}$ to 2000 min$^{-1}$. The condition of the machine was assessed by the operator as 'good state' during the entire period of observation. The variations of the signals and the associated scatter are clearly visible over the rotational speed range considered. The variations in density of the random sample distribution result from the manner in which the machine is operated; that is, the rotational speed values do not all occur with the same frequency.

In order to determine the dependence on the rotational speed, rotational speed classes are usually constructed; upper and lower warning and alarm values are then specified for these classes. Since, of course, the diagnosis is not reached solely on the basis of a single vibrational parameter, the necessity of defining 100 or more limiting values for a machine can result very quickly. It is immediately obvious that a monitoring procedure of this kind cannot provide an acceptable solution for the plant operator, since the frequent occurrence of false alarms can be expected from the start.

\[\text{FIGURE 1: Amplitude of the shaft vibration for 700 measurement over a period of 5 month}\]

Especially with the occurrence of eigenfrequencies in the operational rotational speed range, effective monitoring of variations within a rotational speed class is impossible. For
an excess in amplitude by a factor of 8 at resonance, the limiting values must be adjusted in such a way that a change in amplitude by a factor of 8 to 10 at about 620 min\(^{-1}\) does not trigger an alarm. An unacceptable approach would be a pronounced increase in the number of rotational speed classes in order to improve the adaptation of the limiting values to match the respective curve shape. The representation of characteristic values in terms of magnitude and phase, as applied by many manufacturers, can also present considerable problems in the case of rotational speed fluctuations, since the system becomes insensitive to variations in either phase or magnitude, if these values vary within a rotational speed class.

However, the classification algorithm which represents the random samples in hyperelliptical membership functions, as described in section 3, also fails to provide a suitable tool for dealing with problems of this kind.

The new classification algorithm presented in this article derives the membership function on the basis of a pattern. For this purpose, the function is not described by a few parameters, such as the prototype, scatter, etc.; instead, all random sample elements determine the distribution of the membership function in accordance with a physical load model.

For an arbitrary test vector, \(\vec{x}\), the membership is defined by the following function:

\[
\Phi_c(\vec{x}) = \sum_{n=1}^{N} \frac{1}{1 + (\vec{x} - \vec{x}_n)^T \Sigma_n (\vec{x} - \vec{x}_n)}. \tag{3}
\]

Locally, the membership function is adapted to match a complex random sample distribution by means of an appropriate selection of an inner product with the use of an arbitrarily selected, symmetric, positive-definite weighting matrix, \(\Sigma\). In the presence of several classes, for instance, this matrix can be specified in such a way that the reclassification rate is minimised. The use of a local covariance matrix, which can be sharply defined in the case of unambiguously classified learning sets, or in a fuzzy manner, is also plausible:

\[
\Sigma = \frac{\sum_{i=1}^{K} \mu_{lc}^m (\vec{x}_i - \vec{r}_i)(\vec{x}_i - \vec{r}_i)^T}{\sum_{i=1}^{K} \mu_{lc}^m}; \quad m > 0, \tag{4}
\]

\(\vec{r}_n\) thereby denotes a fuzzy reference vector for the local environment of the random sample point, \(\vec{x}_n\):

\[
\vec{r}_n = \frac{\sum_{i=1}^{K} \mu_{lc}^m \vec{x}_i}{\sum_{i=1}^{K} \mu_{lk}^m}. \tag{5}
\]

The structure of the function \(\Phi\) thereby depends on the size \(K\) of the selected substructure with the random samples, \(l = 1, \ldots, K\).
A procedural sequence for obtaining a membership function $\Phi$ for the purpose of classifying an arbitrary test vector $\tilde{x}$ can be summarised as follows:

1. Determine the $K$-nearest neighbours for all random samples of a class $\Omega_c$.
2. Calculate an appropriate local weighting matrix $\Sigma_n$ for all random samples on the basis of these neighbours.
3. Store each point \( \mathbf{z}_n \) in memory with the associated matrix, \( \Sigma_n \).

4. Determine the membership function \( \Phi_C \) for an arbitrary vector \( \mathbf{z} \).

5. Repeat steps 1 to 4 for all classes.

6. Classify the pattern in class \( \Omega \) with the highest membership, \( \Phi \).

Since the elaborate computational steps, 1 to 3, are necessary only during the design phase of the classifier, no time problems are encountered, even for on-line applications. In figure 3, the excellent matching of the membership function with the random learning sample by the cuts of constant membership for \( \Phi \) is evident, and the function \( \Phi(x) \) is plotted over the scaled feature range in \([0,1]\). The membership function calculated for each value of the rotational speed and amplitude is plotted in figure 4. For appraising an unknown condition, the rotational speed and amplitude are inserted into the function, and the membership value is determined. On the basis of this value, a machine condition is then specified.

A further problem in designing of monitoring systems is the question of how to cover all essential areas of the feature space in defining the membership function, since the efficiency of every classification system depends decisively on the quality of the condition classes defined in a learning process. For elaborate, complex machines integrated in a continuous production process, learning sets for damage conditions can be specified only to a very limited extent, of course, since it usually would be absurd to deliberately damage machines for the purpose of describing damage in a plant. In contrast, values which characterise a normal condition can frequently be measured without problems. The advantage of the classification algorithm developed here is the possibility of defining memberships even if only a single condition class is specified as learning sample. Thus, the fall of a membership value below a specified limit is a reliable indication of an altered operating condition. From figure 3, it is evident that all data of the learning set assume a membership value greater than two. The limit curve plotted for values \( \Phi \) equal to unity could be employed as a warning value. If the membership falls below a value of 0.5, an alarm would then be triggered.

6 CONCLUSIONS

Advances in instrumentation and computer information processing technologies offer new possibilities for the condition monitoring of rotating machinery in nuclear power plants. The focus is shifting from how to obtain rotating machinery to new methods for interpreting the information. Based on the experience in a plant of the primary chemical industry where a diagnostic system developed for machines with constant rotational speed has been in service for more than four years, and the efficiency has been repeatedly demonstrated by the detection of various faults in due time, we present a modified classification approach. This monitoring system is available as a prototype and has previously been tested off-line with data measured on a recirculation pump in a German nuclear power station. The results thus achieved are very promising; hence, this method offers an appropriate solution for monitoring rotors with variable rotational speed.
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