AN INTEGRATED, SOFT COMPUTING APPROACH FOR MACHINE CONDITION DIAGNOSIS

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ABSTRACT: Machine fault diagnosis, based on vibration measurements is a formidable task which calls for reliable data analysis and decision making under the presence of uncertainty. The diagnosis task is complicated by the noise usually present in the measured quantities, the lack of a clear deterministic relationship between the measured quantities and the machine state, the different characteristics of the transmission path between the error point and the measurement location and the variations of the observed vibration on different machine configurations. Neurofuzzy computing has recently emerged as a viable problem solving approach which fuses the learning capabilities of neural networks with the transparency and the representation power of fuzzy inference systems. This paper presents preliminary results of neurofuzzy methods applied to rotating machinery fault diagnosis, as part of the VISION project (BRITE/EURAM BE95-1313).

1. INTRODUCTION
The VISION project approach recognises the need to utilise various sources of information, including simulated, test rig and real plant data into an integrated hybrid diagnosis system that is essentially data-driven. The overall system employs a variety of data analysis and decision making techniques such as statistical analysis, neural networks and rule-based systems, appropriate for different kinds of tasks such as recognition of fault type or fault severity estimation for a range of machine types (Jantunen et al. 1997). In addition to these methods, soft-computing techniques based on fuzzy logic and are currently also being investigated. Fuzzy systems can simultaneously handle both numerical and linguistic information. Integrated hybrid fuzzy-neural representations or inherently fuzzy logic models equipped with neural network like learning capabilities are powerful adaptive modelling tools which combine the individual merits of both fuzzy logic systems and neural networks. Some attempts at integrating neural and fuzzy systems approaches for machine condition diagnostics are reported in the literature. A hybrid neural-fuzzy synergistic strategy for detection of rolling element bearing faults is reported, where important vibration spectral features are described by means of fuzzy membership functions which are then fed into a Kohonen self-organising map which categorises them into faulty or healthy condition (Loskiewicz-Buczak and Uhrig 1993). Fuzzy membership functions for rolling element bearing fault classification were also defined by employing an empirical quantification of the sensitivity of specific vibration spectral features to faults (Liu et al. 1996). The fuzzy classification was found to perform very well when tested on real data derived from a specific machine. In another application, fuzzy logic techniques facilitated the intuitive quantification of vagueness relevant to the definition of the predominant frequencies. The basic idea behind that is that a user often characterises frequencies as 1xRPM and 2xRPM but in practice these frequencies are ambiguously defined due to the lack of clear boundaries between neighbouring frequency bands in practical signal acquisition situations (Siu et al. 1997). In the above application, fuzzy granulation has also employed to describe the severity of a symptom in linguistic terms such as low, close to limit and high. The fuzzy rule base design though was based on available expert knowledge, without provision for optimisation on the basis of available vibration data. A hybrid neural-fuzzy diagnostic system for roller element bearing fault detection has also been reported where a fuzzy logic module and an Adaptive Resonance Theory (ART) based neural module complement each other in performing the diagnosis task (Huang and Wang 1996). Despite the significant successes of employing hybrid neural-fuzzy systems for machine condition monitoring and diagnosis, based on vibration data, most approaches are still rather specialised and fragmented and considerable amount of research is still needed in order to achieve generic, computational intelligence based solutions to machine fault diagnoses problems. This paper describes the first steps taken towards this direction, under the framework of VISION, a large European research project (BRITE/EURAM BE95-1313).
2. NEUROFUZZY COMPUTING

Neurofuzzy computing aims at integrating the computational merits of neural networks, largely associated with their learning capability, and the representation power and transparency of fuzzy systems. The general functionality remains that of a pure fuzzy system, which is mapped onto a network structure. What varies from one implementation to another is the definition of individual elements of a fuzzy system. Thus, neurofuzzy approaches can feature:

- different definitions of membership functions such as Gaussians or B-splines (Brown and Harris 1995)
- consequent parts of the fuzzy rules defined either as output fuzzy sets or as functions of the inputs.
- singleton or non-singleton (Mouzouris and Mendel 1997) fuzzification.
- different fuzzy reasoning mechanisms and fuzzy operators (Zhang and Kandel 1998)

Which individual choice works better often depends on the application targeted. For example, Gaussian membership functions are very flexible, can offer smooth approximations and are infinitely differentiable. B-splines on the other hand have strictly compact support and therefore can be locally optimised. They also naturally form a partition of unity, particularly useful for preserving model transparency and facilitate the definition of relationships between rule weights and confidence factors (Brown and Harris 1995, Bossley 1997). When the consequent parts are functions of the inputs, better approximations can be achieved. However, the transparency of the resulting models is becoming increasingly dubious as the dimensionality of the problem and the size of the rule base increase. Singleton fuzzification is computationally simpler but nonsingleton fuzzy systems may be more appropriate to handle inputs uncertainty (Mouzouris and Mendel 1997). Fuzzy reasoning mechanisms can yield different results depending on the fuzzy operators involved and there are problems where a distinction between pessimistic or optimistic interpretation of fuzzy rules can be useful (Zhang and Kandel 1998).

This paper examines the applicability of B-spline based neurofuzzy models for fault diagnosis in rotating machines. The theoretical properties of B-spline modelling of observational data are examined in (Weyer and Kavli 1997), while functional equivalences between fuzzy inference systems and spline-based networks have been established in (Hunt et al. 1995). B-splines are piecewise polynomials of desired order. B-spline based fuzzy membership functions are recursively defined for any given knot vector \[ \lambda_i, \lambda_{i+1} \ldots \lambda_{n+i} \] and order of splines according to:

\[
N_{i+1}^{(r)}(x) = \begin{cases} 1 & x \in [\lambda_i, \lambda_{i+1}] \\ 0 & \text{otherwise} \end{cases}, \quad j \in [1,n-1] \cap \Re
\]

\[
N_i^{(r)}(x) = \frac{x - \lambda_{i+1}}{\lambda_{i+1} - \lambda_{i+2}} N_{i+1}^{(r)}(x) + \frac{\lambda_i - x}{\lambda_{i+1} - \lambda_{i+2}} N_{i+2}^{(r)}(x), \quad j \in [k,n + 2k - 3] \cap \Re
\]

where \( k \) is the order of splines, \( n \) is the number of internal knots, \( n_e \) the number of external knots, \( n_e = 2 \cdot (k - 1) \), and \( r \) is the number of defined membership functions, in which \( r = n + k - 2 \). An example of B-splines based neurofuzzy network is shown in Figure 1. The general form of a fuzzy rule in a B-spline neurofuzzy network is:

\[
R^{(j)}: \text{IF } u_1 \text{ is } F_{i}^{(1)} \text{ and } \ldots \text{ } u_n \text{ is } F_{i}^{(n)} \text{ THEN } v \text{ is } G_{c}^{(j)} (c) \text{(univariate form)}
\]

\[
R^{(j)}: \text{IF } u \text{ is } F_{i}^{(j)} \text{ THEN } v \text{ is } G_{c}^{(j)} (c) \text{(multivariate form)}
\]

where \( j = 1,2,...,M \), \( M \) is the number of fuzzy rules in the rule base, \( F_i \) are the input fuzzy sets associated with the \( j \)-th fuzzy rule defined in \( U_j \subset \Re \), \( G_i \) is the \( k \)-th output fuzzy set defined in \( V \subset \Re \) (\( \Re \) denotes the set of real numbers), \( c_{jk} \) is the confidence that the \( j \)-th fuzzy rule attributes to the \( k \)-th output fuzzy set, \( u = [u_1, u_2, \ldots, u_n] \in U_1 \times \ldots \times U_j \times \ldots \times U_n \), and \( v \in V \). \( u \) and \( v \) are linguistic variables. Their numerical values are \( x = [x_1, x_2, \ldots, x_n] \in U \) and \( y \in V \) respectively. It has been shown (Brown and Harris 1995) that for B-spline input membership functions, singleton fuzzification, algebraic operators used for fuzzy conjunction and disjunction, centre
of gravity defuzzification and normalised rule confidences the output of the neurofuzzy network is:
\[ y(x) = \sum_{j=1}^{n} \mu_{\alpha_j}(x) \cdot w_j, \]
where \( \mu_{\alpha_j}(x) \) is the multivariate input fuzzy sets, corresponding to the \( j \)-th rule. The relationship between weights and rule confidences for symmetrical output fuzzy sets are (Brown and Harris 1995):
\[ w_j = \sum_{k=1}^{n} c_{\beta_k} y_k^j, \quad c_{\beta_k} = \mu_{\beta_k}(w_j), \]
where \( y_k^j \) is the centre of the \( k \)-th output fuzzy set, \( n_x \) the number of fuzzy output sets and \( \sum_{k=1}^{n} c_{\beta_k} = 1 \). The neurofuzzy toolbox of Neuframe (Neural Computing Sciences) data-analysis and modelling package is used for model construction. It employs an evolutionary algorithm for additive neurofuzzy models construction, which performs a series of model refinements such as univariate sub-network addition or deletion, sub-models tensor product or split, knot insertion or deletion, spline order reduction and regularisation in order to construct reduced size neurofuzzy models (Brown et al 1997), an approach similar to that of ASMOD (Weyer and Kavli 1997). An important feature of B-spline based neurofuzzy models is the existence of an invertible relationship between fuzzy rule weights and rule confidences (Brown and Harris 1995). This feature is of vital importance when evaluating the neurofuzzy system outputs. The overall process very effectively results in a compact neurofuzzy representation which performs active input selection and features a fuzzy systems transparency.

3. DESCRIPTION OF THE INTEGRATED, COMPUTATIONAL INTELLIGENCE APPROACH

The VISION project aims at developing an intelligent, adaptive monitoring and diagnostic system for rotating machinery. Based on vibration data, the system employs various artificial intelligence, statistical and simulation techniques, in order to achieve a high level of equipment reliability (Adgar et al. 1998). An additional approach currently under development examines the application of integrated soft computing techniques and in particular fuzzy logic and neurofuzzy computing methods for performing fault diagnosis. A schematic diagram of the soft computing approach, within the framework of the overall VISION project is shown in Figure 1. The system inputs are the parameters extracted from the time series and spectral representation of the vibration signal. The parameters selected are those likely to contribute some information relevant to faults for the particular machine type under consideration. It is intended that the machine type classification will be performed according to MIMOSA specifications (Mechanical Device Segment Types) (Mitchell 1996). At the core of the diagnosis system are intelligent diagnosis modules for each machine type. These modules are capable of performing fault diagnosis, i.e. fault type recognition and fault severity estimation, while at the same type a measure of the certainty about the diagnosis outcome will be provided. A brief description of the functionality of the diagnosis modules follows.

4 FUNCTIONALITY OF THE DIAGNOSIS MODULES

Depending on the machine type, the relevant spectral and time series parameters are fed into the appropriate diagnosis module. The diagnosis decision is reached as the result of co-active function of several different fault recognition and fault modelling sub-modules, in order to achieve higher reliability and robustness. The vibration signal parameters are processed in two different ways, fault type recognition and fault severity estimation. The fault models may have different requirements in terms of data pre-processing, as a set of extracted features adequate for data representation may exhibit poor discrimination power and vice versa. Employing fuzzy reasoning, the fuzzy fault classifier provides

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**Figure 2. Schematic Diagram of the Intelligent Diagnosis System**

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with an initial diagnosis of the machine condition. Instead of performing a "hard" classification (i.e. accepting that a fault either exists or not at all) the classifier will be able to attribute membership values for each fault type. It is anticipated that this will be particularly beneficial in cases of multiple faults or noisy input data. The Fault Models sub-module consists of a series of different fault models (neural network, neurofuzzy, rule-based) and a polling module which examines the relative agreement between the individual models in order to provide a final estimate of the fault type and severity. An optional feature is the capability of switching between models as a result of the fuzzy fault classification. Finally, the outputs of the fault models together with the membership values for each type of fault, are combined into a single Fault Model Aggregation module, which provide the final diagnostic outcome.

5. NEUROFUZZY FAULT CLASSIFICATION

The first stage towards developing an integrated, soft computing approach for machine fault diagnosis is to define a fuzzy fault classification strategy. A fundamental aspect of the VISION project approach in developing diagnosis strategies is the use of different sources of data in order to come with sufficiently rich vibration data sets to facilitate data-driven model building. Real data is often scarce and does not provide enough information to cover the whole operation range of the modelled machinery. The VISION project utilises two additional sources of artificially created vibration data, derived from a Finite Element Model simulator and a Simple Fault Simulator (SFS), developed by VTT in Finland. The simulation models are verified using data acquired from a purpose-built test rig and actual machines at VISION project user sites, in order to ensure that the simulated data is as close as possible to the observed data. The test rig (Figure 3) of the first stage of the project consists of a motor, brake and a shaft with two bearings. The test rig was used for modelling common faults such as unbalance, misalignment and different types of bearing faults. Details about the Simple Fault and Finite Element Model Simulators can be found in (Jantunen and Vähä-Pietilä 1997). Data sets from the SFS were used in order to construct neurofuzzy models for performing fault classification. These sets comprise data contaminated with noise and corresponding to single fault scenarios. The size of the three pattern sets (training, evaluation and validation set) employed in the network construction and validation was 683 patterns. The neurofuzzy construction algorithm had actually to select among approximately 50 inputs, in order to build neurofuzzy classification networks for each individual fault type. Neuframe provides with a variety of information criteria to assist model construction such as Generalised Cross Validation, Structural Risk Minimisation (SRM). Among the above, SRM was found to yield compact neurofuzzy architectures, without sacrificing much in terms of classification accuracy. However, the large number of the input variables, limits in practice the ability to perform an exhaustive test of all the above criteria over the present problem, due to computational time limitations. The performance of the derived classifier was assessed over SFS simulated data, which was never used before for model construction purposes, thus providing an individual assessment of the neurofuzzy model performance. The overall correct classification performance was approximately 88%. However, B-spline neurofuzzy models can offer together with their output a certainty factor about the outcome. If only the cases with a certainty factor higher than 50% are examined, which amounts to 76% of the validation patterns, then the classification performance becomes over 98%. This is a significant result, considering that the data employed for model construction were contaminated by noise. Thus more reliable classification is achieved. Table 1 summarises the results for each individual fault type. In most cases apart from train faults, the classification performance was very good.

<table>
<thead>
<tr>
<th>Pattern with higher than 50% certainty</th>
<th>Correctly classified among those with certainty &gt; 50%</th>
<th>Correctly classified over the whole validation set</th>
<th>Total Number of Patterns</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unbalance</td>
<td>182</td>
<td>186</td>
<td>189</td>
</tr>
<tr>
<td>Outer Race Defect</td>
<td>28</td>
<td>31</td>
<td>36</td>
</tr>
<tr>
<td>Train Fault</td>
<td>1</td>
<td>5</td>
<td>40</td>
</tr>
<tr>
<td>Inner Race Defect</td>
<td>41</td>
<td>41</td>
<td>42</td>
</tr>
<tr>
<td>Misalignment</td>
<td>157</td>
<td>163</td>
<td>166</td>
</tr>
<tr>
<td>Ball Defect</td>
<td>26</td>
<td>30</td>
<td>38</td>
</tr>
<tr>
<td>Healthy</td>
<td>81</td>
<td>144</td>
<td>172</td>
</tr>
<tr>
<td>Total</td>
<td>516</td>
<td>602</td>
<td>683</td>
</tr>
<tr>
<td>(percentage over the total number of validation patterns)</td>
<td>(percentage over the total number of validation patterns)</td>
<td>(percentage over the total number of validation patterns)</td>
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</table>
6. CONCLUSION
This paper described the first steps taken towards the development of an integrated soft computing strategy for rotating machinery fault diagnosis, based on vibration data, as part of the VISION project. The main motivation for applying a neurofuzzy computing approach is that it combines the computational merits of neural networks with the representation power and transparency of fuzzy inference systems. This is particularly beneficial as the models developed can learn from or adapt on the basis of vibration data. The learned knowledge is stored in the network structure in the form of fuzzy IF-THEN rules, thus providing the user with an insight as to why each individual diagnostic decision is taken. Further research is currently looking into ways of improving the derived models, the development of neurofuzzy models for multiple faults, as well as testing and adaptation of the models, based on real-life (test-rig and project end-user sites) data. The same stages will be followed for more complex machinery examined in the next phases of the VISION project. Ultimately, the architectures developed will be put into the more general framework of the hybrid intelligent diagnosis system currently under development in the University of Sunderland and will be integrated with other intelligent diagnosis modules such as neural networks and rule-based or neural-expert systems in order to achieve highly reliable and robust machine condition diagnoses.

ACKNOWLEDGEMENTS
The authors wish to acknowledge all the VISION project partners for all their efforts and their excellent collaboration, as well as the EU for the financial support to the project.

REFERENCES
Adgar, A; Cox, C; MacIntyre, J. 1998. Automatic fault diagnosis for rotating machinery using statistical and neural network techniques. To be presented at the 11th International Congress and Exhibition on Condition Monitoring and Diagnostic Engineering Management, COMADEM 98, Launceston, Tasmania, Australia.
Jantunen, E; MacIntyre, J; Jennings, I; Development of a Hybrid Expert System using Simulations and Neural Networks Proc. of EUFIT 97, Vol 3, pp.1694-1698 , Aachen, Germany
Jantunen, E; Vähä-Pietilä, K. Simulation of Faults in Rotating Machines Proc. of COMADEM 97, Vol 1, pp283-292, Helsinki, Finland