FAULT DETECTION SYSTEM FOR CENTRIFUGAL PUMPS USING NEURAL NETWORKS AND NEURO-FUZZY TECHNIQUES

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Abstract :
This paper describes a diagnosis system for centrifugal pumps that was developed in the framework of pump maintenance project between CETIM (Centre Technique des Industries Techniques) and UTC (Université Technologique de Compiègne). The system is based on vibration measurements, signal pre-processing and classification with pattern recognition approaches. Experiments were conducted on an actual pump assembly to acquire operational vibration signals resulting from various induced faults included in our diagnostic interests. A feature vector of pertinent parameters was first identified using signal processing techniques. Because of the type of faults of interest (misalignment, cavitation, partial flow, and air injection) both kinematics and statistical descriptors were used to define a pertinent feature vector to be used in the classification scheme. Neural Networks structures exhibit some limits to classify some 'unlearned' levels of gradual faults such as partial flow or cavitations. Hence the idea was to use neuro-fuzzy models. This allowed providing a decision through optimized membership functions which handles more efficiency the gradual faults levels. All the process (measurements, learning, classification) has been implemented in real time in Labview / Matlab environment.

Keywords : Vibrations, pump diagnosis, classification, feature vector, neural networks, neuro-fuzzy

1. Objectives

Due to the heavy breakdown costs (on repairing) for rotating machines such pumps, the early fault detection becomes an industrial priority through the increasing of investments on diagnosis solutions. Operational efficiency of these solutions is generally evaluated on the accuracy of the diagnosis as well as the influence of the required experimental devices on machine operation. Following these criteria, diagnosis based on vibratory analysis seems to be the most reliable way to monitor pump state. Considering the various faults that have been identified as critical, and for which the vibrations symptoms are difficult to establish, neural networks classification approach have been chosen for the decision making.

More specifically, the study intends to develop a real-time fault detection tool for centrifugal pumps using neural and fuzzy techniques and focuses on several faults :

- Partial flow rates,
- Loosening of front/rear pump attachments,
- Misalignment,
- Cavitation,
- Air injection on the inlet,
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figure 1: Centrifugal pump test bench (CETIM)

2. Experimental test bench

The study was conducted on an industrial scale pump of CETIM in Nantes (figure 1) and the following tasks were studied :

- extraction of the vibration symptoms for each fault using signal processing and statistical techniques,
- test of the feasibility of neural networks to identify the pump state from the vibration acquisition and assessing the possibility of improving performances with fuzzy techniques
- implementation of a real-time diagnosis process using only one accelerometer and an acquisition card linked to Labview and Matlab.

The adopted strategy consisted on a short simulation of fault symptoms on a centrifugal pump installation in order to record the signals of its vibratory behavior. This, to form a representative knowledge database used on training neural networks structures, able to characterize a fault occurrence. The diagnosis domain is extended to the following states :

- partial flow rates (0, 20, 40, 60, 80, 112, 128% of nominal flow rate: 250 m^3/h)
- loosening of front/rear fixing
- misalignment
- cavitations (1, 3, 6% of NPSH)
- air injection on the inlet (9, 15 l/min)
- no faults

Finally, the system should be able to detect 15 types of machine anomalies. The ‘no faults’ case presents unsteady vibratory state, that is why we made signal acquisition of normal operation after each fault simulation.

In the following, we will firstly explain our approach to exploit neural networks and neuro-fuzz techniques in fault detection application. Then, characteristics of the implemented solution will be presented and illustrated through interfaces.

3. Neural networks and neuro-fuzzy techniques for pump diagnosis

3.1 Faults detection system based on neural networks

Pump vibratory analysis has shown variations between different types of machine malfunction which can be expressed through some parameters extracted by signal processing. Even if these parameters provide useful information for faults detection, it is ridiculous to make decision based on simple rules. Measurement uncertainty, lack of deterministic relationships between parameters and especially the availability of vibrations data have urged us to use Artificial Neural Networks, a knowledge-based tool that many previous works proved its effectiveness for identification and classification applications.

In fact, a neural network is an information processing model that mirrors the organization and mechanism of the human brain (a network of over 10 billion neurons) based on learning and memory. It operates as a set of interconnected automats called neurons which can be adapted to carry out specific tasks by providing empirical knowledge through a learning cycle. The most common architecture of neural network is made up of three layers of neurons: input layer, hidden layer and output layer. The input layer receives external data and is joined to the hidden layer by connectors which are assigned weights called synaptic coefficients. The values of the input data is multiplied by its appropriate weights and summed within the hidden layer. The sum is then converted through a non-linear function usually called sigmoidal function to an output value received by the output layer where decision is made. Like its biological origin, neural networks need the ability to 'learn' information as opposed to being 'programmed'. This learning ability is accomplished through training of the network by providing reliable and correct examples called empirical knowledge. Learning process seeks to optimize connections weights. Its cycle consists on introducing an example (input), computing its output value and comparing it to desired results and updating weights. This cycle is repeated until the network presents satisfying performances in the classification of knowledge database examples. For further information about neural networks, you can refer to [1]. In the following, we will focus on explaining the process of applying neural networks for fault detection of centrifugal pump.

This process is performed through two main steps :

- *Data pre-processing*: it aims to determine feature vector which conditions the discriminating ability of neural network between the pump configurations. Parameters of feature vector were extracted from machine vibrations with time and spectral analysis. Even if statistical parameters, computed from time signal, provide interesting information; it is basically in the spectrum where fault effects are better expressed in terms of energy level and distribution in the bandwidth. In order to reduce the neural network complexity, the feature vector was optimized from 26 to 13 parameters by data analysis methods (Fischer, PCA and FDA). In addition, vibrations signals were sampled with 50 KHz and five-minute recording of each pump faults configuration was enough to have a significant database of feature vector samples which represent the required knowledge to build our neural classification system.

- *Neural network modeling*: once pre-processing is done, we should exploit discriminating effect of feature vector by selecting an appropriate neural network structure. For our diagnosis application, we used the Multi Layer Perceptron (MLP) model, very adapted to realize separation between classes. This choice is also justified by the supervised learning that can be easily applied in MLP structure. In fact, we can distinguish, in our signals database, the sub-database of each fault. Therefore, we previously know, for each input example, the target output which enhances the use of supervised learning.

The followed strategy consists of associating one MLP for each fault detection process. So diagnosis system will contain a total of 16 MLP (15 faults + 'no faults'). In fact, despite its complexity, this strategy has presented better performance than the other tested strategy where we apply a single MLP with 5 outputs to ensure the whole detection process. Each MLP should give an accurate decision about presence or absence of its assigned fault so that final pump state can be deduced from all MLP responses. The three layers of MLP structure were defined as following:

- 13 input neurons: represent parameters of feature vector
- X hidden neurons: the adequate number could not be mathematically determined but only estimated for each MLP from the database examples. The number of hidden neurons is as much more important for an MLP of a given fault as its feature vector parameters are partially confounded with those of other faults
- 1 output neuron: its activation process returns boolean value that gives the network response

The connections values of this structure are randomly initialized until learning process takes place. No doubts, learning process is the most significant attribute of neural network technique that creates its added value through finding the accurate weights combination. This combination is determined by some rules defined within a learning algorithm. Back-propagation algorithm is the most suitable for our MLP structure in a context of supervised learning. It targets to minimize, through iterative modification, the $E(t) = \frac{1}{2}\sum_k (d_k - y_k)^2$ following quadratic error function:

d_k: target output y_k: output response where k browses all training set

Learning process is validated when the algorithm reaches steady state which can be assessed by many criteria as error convergence or the rate of good classification. Learning database is constituted of about 3500 samples including signal acquisitions from 21 acquisitions (15 for faults and 6 for 'no faults'). The validation of learning performances occurred with a test database of about 1500 samples (independent from learning ones). Learning performances are sumarized on the table I.

3.2 Evaluation of neural networks results and improvements

As shown table I, the test of learned NN gives a rate of correct classification of about 99% for each fault. If we suppose that all wrong classified samples are distinct, the global rate of the system correct response is about 96% which proves that neural networks are efficient for detection of faults for which database contains learning samples.

However, final solution should satisfy two main specifications:

- Automation of procedures leading to build the required in an optimal time (acquisition, database forming and controlling neural network learning)
- Reliable and intelligent fault detection with approximation capacities

Table I : performance of the NN classifier

Faults	Hidden neurons	Number of iterations	Number of wrong classified	Rate of correct classification
Partial flow: 0%	10	200	0	100%
PF: 20%	10	200	0	100%
PF: 40%	15	300	0	100%
PF: 60%	25	2500	0	100%
PF: 80%	25	2000	1	99.93%
PF: 112%	60	5400	5	99.67%
PF: 128%	10	300	0	100%
Misalignment	15	34900	5	99.67%
Rear fixing	5	300	0	100%
Front fixing	10	1300	1	99.93%
Cavitations 1%	30	20200	4	99.73%
Cavitations 3%	30	36200	8	99.47%
Cavitations 6%	30	42300	4	99.73%
Air injection 9l/mn	30	49000	24	98.42%
Air injection 15l/mn	30	12100	1	99.93%
No faults	30	97000	18	98.82%

Tests on this system have shown limits on the detection of ‘unlearned’ gradual faults states. For example, we established that neural network finds difficulty to detect intermediate NPSH cavitations level between the learned ones (1, 3 and 6%). The same observation concerns partial flow levels, where for example, simulation of 50% flow is often rejected and not approached on the system with a decision of 40% or 60%. To overcome these limitations, it was decided to use neuro-fuzzy techniques in order to improve gradual fault detection.

3.3 Introduction of neuro-fuzzy technique

Neuro-fuzzy systems are defined as a combination of neural network with Fuzzy Inference System (FIS). Unlike learning mechanism of neural network, FIS implements a non-linear mapping from the inputs to outputs space with a set of if-then rules. To be more specific, let’s outline FIS process in 3 operations :

- fuzzification: using membership functions, each input is assigned to each state with membership degree
- inference: “If-then” Rules will be applied to input variable based on their membership degree to obtain those of output variables
- defuzzification: from output membership degree, we apply a decision criterion to compute system response

These operations show that fuzzy reasoning based on membership and rules could overtake black box operating of neural networks and integrate interpretation ability. However, the application complexity does not allow using a stand-alone FIS where rules are building with human expertise. An automation process is needed to generate accurate rules. Here comes the importance of complementarity between neural network and FIS ensured by neuro-fuzzy. In fact, this hybrid structure model FIS operations in neural network architecture. By this way, “if-then” rules will be organized through connections between neural network layers and especially optimized with the learning process. The learning process will target to find membership functions parameters that give best performances.

Neuro-fuzzy technique was applied in our application for two gradual faults: NPSH cavitations and partial flow rate. It aims to detect any cavitations or flow level and assign it with the most accurate decision from our diagnosis plate form (1, 3 or 6% for cavitations and 0, 20, 40…128% for flow rate). Our procedure to prepare a neuro-fuzzy system includes the following steps :

- *reduction of input space*: Considering that complexity of the learning algorithm in neuro-fuzzy raises exponentially with the size of feature vector, it was necessary to reduce number of input from 13 to 2 or 3 at most. In other words, supposing that our FIS have p membership functions and q inputs, means that p^q rules will be generated and then p^q hidden neurons will be created for our model. Therefore, feasibility constraints urged us to optimize feature vector size by discriminant analysis based on Fisher criterion. The idea of Fisher criterion is to find a linear combination of input variables that simultaneously minimizes group’s dispersion around their means (intra-classes inertia) and maximizes groups means separation (inter-classes inertia). That’s allowed an input space transformation to a new space where almost discriminatory contribution is held by few variables (principal axes). The application of this approach to partial flow dataset reduced feature vector size from 13 to 3 parameters ensuring about 97% of information. Fig3 shows contribution of the first parameter in classes’ separation.

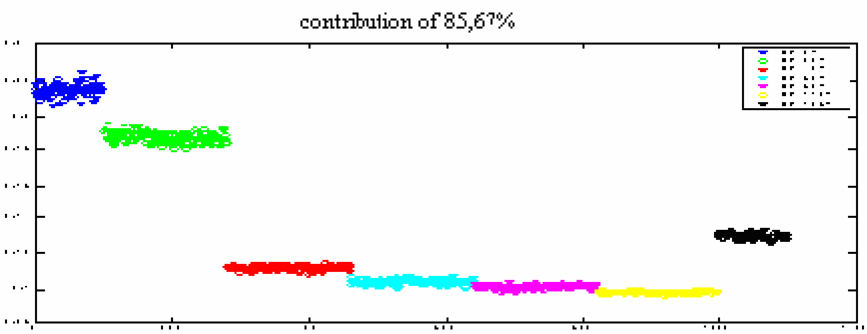

Fig3. Contribution of 1st parameter for partial flow rate

- *classification with neuro-fuzzy system*: Like neural network, neuro-fuzzy modeling requires structure building and learning. Following separation behavior between classes of each of the selected inputs, we assigned as membership functions for partial flow case: 7 Gaussians for 1^{st}, 3 for 2^{nd} and 2 for 3^{rd}. Using Fuzzy logic toolbox of Matlab environment, we can generate automatically 7*3*2=42 if-then rules treating all possibilities which is negligible comparing to rules number when keeping 13 inputs. Learning process is achieved by ANFIS algorithm [10] which determines optimal Gaussian functions parameters (center and bias) that minimize error. Tests of neuro-fuzzy systems for partial flow and cavitations were successful. When varying progressively pump flow, we observed that system becomes much more sensitive to transition between a partial flow level to another one and gives good decision for ‘unlearned’ levels.

4. Implementation of a diagnosis system

A final solution is an interactive demonstrator that ensures a real-time centrifugal pump diagnosis. These specifications urged us to use Labview, well-known software in instrumentation and signal processing. In fact, Labview offers required tools to create interfaces adapted to industrial needs. Besides, in this environment, we are able to control acquisition cards, to process data in real time and to run Matlab files with easy interfacing procedures. This last functionality is important especially as all prepared neural networks and neuro-fuzzy were developed with Matlab.
Implementation of the system was done from the signals acquisition, the training phase until the real time classification.

4.1 Acquisition procedure

This procedure ensures a system communication with machine and its particularity is to be simple and economic. Vibrations were picked up by an accelerometer placed in radial direction at 45° to the pump landing in order to have both vertical and horizontal contributions. They are transferred from accelerometer to an acquisition card by the way of conditioning case. The used card NI 4552 is fully compatible with Labview, which make its configuration easier. Once configured, it becomes recognized in our Labview application and a virtual way can be created to model acquired signals.

4.2 System characteristics

The solution can be used for two main tasks:

- Building a set of neural networks and neuro-fuzzy adapted to recognize the pump vibratory behavior
- The use of these structures to operate a demonstrator of faults detection

Even if the basic function (diagnosis) is ensured by second task, the first is added to shorten experiment procedures with automation. In fact, our diagnosis system can be used only for a specific pump characteristic (rotation speed, installation…). By consequence, we are obliged to remake experiments for every different configuration. Therefore, we developed a module that guides the user in building classification structures in optimal time. This module achieves the following operations:

- Signals acquisition and storage: as shown in Fig3, simulation of each fault can be well directed and followed. Moreover, for each acquired signal, parameters of feature vectors are computed and saved on sub-database of the simulated fault.
- Constitution of database: All sub-databases are gathered in learning and test database
- Learning of neural networks and neuro-fuzzy: Thanks to interfacing possibilities of Matlab with Labview, learning process can occur interactively as shown in Fig5. This clear follow-up of learning process allows stopping it and saving structure whenever performances are judged satisfying.

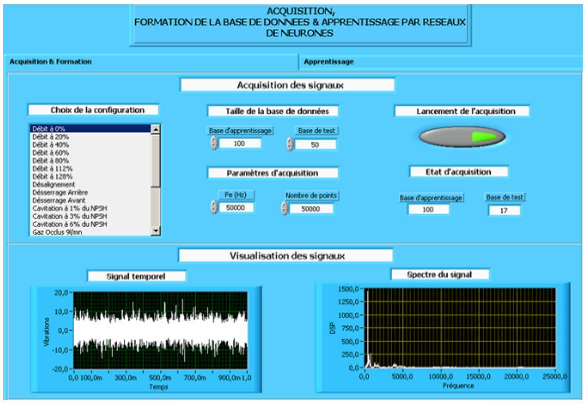

Fig3. Signal acquisition

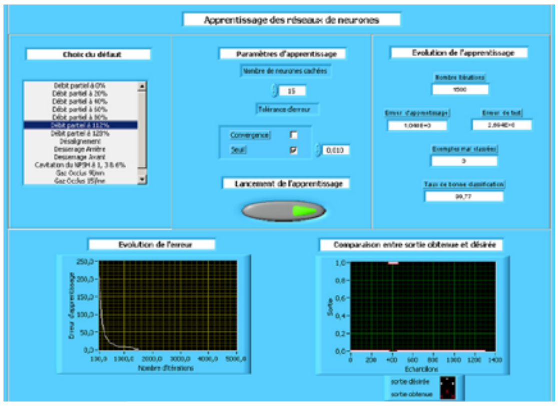

Fig4. Learning process

The diagnosis system will use the validated neural networks and neuro-fuzzy to perform detection process. This process started with the acquisition of a signal sample having the same database's properties. A feature vector will be extracted from this sample and presented as input for each classification structure. From their outputs, decision is made and result will be shown in the demonstrator (Fig5). The detection process will occur real-time with the acquisition so that decision will be updated with each sample. Additionally, each given decision is analyzed through displayers and graphs that compare spectrum and feature vector parameter of the detected state with those of normal machine operation.

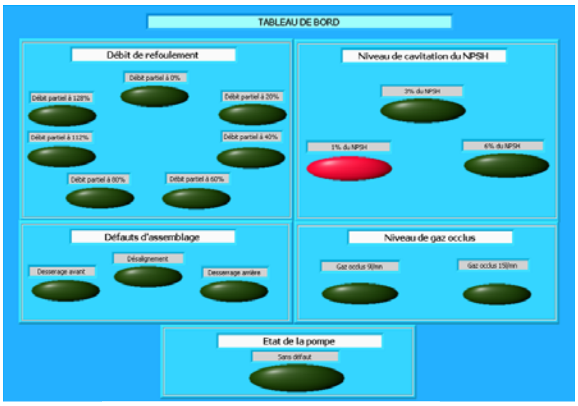

Fig5. Fault detection demonstrator

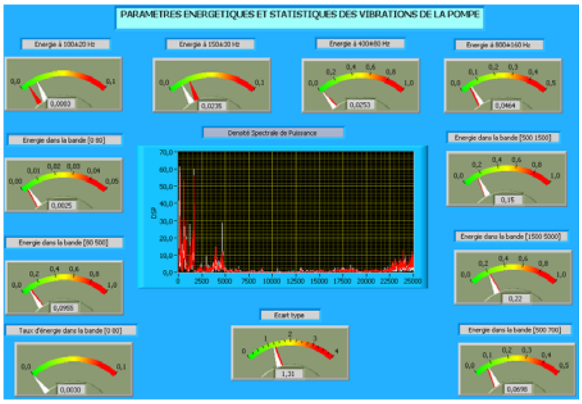

Fig6. Analysis of vibratory behavior

5. Conclusion and perspectives

A Neural Network and fuzzy Neural Network pump diagnostic system have been presented. It was developed in order to reach the goals of pump manufacturers. The requirements were : - the use of only one sensor (accelerometer), - the ability to detect and classify some specific faults for which "models" are not easily available (Partial flow rates, loosening of front/rear pump attachments, misalignment, cavitation, air injection on the inlet), - a simple implementation easy to use.

The system was developed using a Labview / Matlab solution and tested on pump industrial test bench, in CETM Nantes. We developed a system composed of several Networks, one for fault, in order to make easier the learning data in an industrial environment. One interesting point was the use of fuzzy NN in order to take into account the “unlearned” states, especialy for faults with several levels (ex : flow rate from 0% to 100%, etc).
Special attention was put on the performance of the system with varying conditions and we were able to “adapt” some learning data to other running conditions.
This will allows us to use easily the system with others pumps. Work is going on in this direction.

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