Automatic Faults Diagnosis by Application of Neural Network System and Condition-Based Monitoring Using Vibration Signals

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Abstract

Companies invest a lot of effort in predictive maintenance due to the relationship with profit and equipment availability. The principal aim is to predict the occurrence of early faults, allowing repairs to be planned. On the other hand, environmentally friendly practices with higher standards of health and safety in industry can be respected, avoiding breaches of the law. With this aim, a special type of spectrum has been developed that uses fixed frequency bands and vibration severity levels. The special spectrum's data is used in a neural network, which detects a fault in the early stages and an automatic diagnosis is obtained quickly and reliably. This technique is especially oriented to intranet implementation systems to diagnose the real health condition of any rotating machinery in real-time, optimizing both management maintenance and production. It is used in real measurements of rotating machinery vibration, monitoring signals to obtain the results and conclusions about this technique.

Introduction

Presently, the global economy has increasingly led companies worldwide to invest huge amounts in the research and development of diverse, robust, highly dependable, easily maintainable, and available equipment. Such efforts aim at machines with the ability to produce more at lower costs, spread throughout the production chain [1].

The automation, the costs due to break downs, and the non-planning of maintenance is prejudicial to both profit and equipment availability. In this way, the preventive maintenance (PVM) has been optimized by the use of predictive maintenance (PDM), or sometimes PVM is changed by PDM. So, the PDM methodology is becoming common in condition monitoring and diagnosis of faults in rotating machineries where the main goals are to optimize the maintenance schedule and to avoid premature breakdown.

When PDM techniques are applied, the management of the productive system is improved because it becomes possible to follow the performance of equipment for the simple monitoring of a variable, as is the case with vibration. Therefore, a many companies employ experts with the knowledge to monitor and to diagnosis faults [2].

The production of electrical energy is important for the development of every nation. A large number of factories, industries, and societies use this kind of energy to survive. In countries where there is a great hydraulic potential, like Brazil, it is very common to find hydropower plants, such as Itaipu, Tucuruí, and Ilha Solteira. These are bigger plants (where more than 1,000 MW of power are generated), but the hydraulic potential utilized by this kind of plant is almost depleted; also, the environmental impact caused during the current building of this lagoon, barrier, and other factors are relevant. Nowadays, smaller plants (where less than 20 MW are generated) are becoming popular due to the fact that they have less environmental impact during their construction, and Brazil is utilizing the hydroelectric potential in a positive manner. In this context, the same operator is responsible for two or more small hydropower plants. These plants are in far and remote places in different states of Brazil. For monitoring these plants, the special intranet system has been implemented where all data from each plant is transmitted to a main center that optimizes the management in this kind of hydropower plant. The illustration of this special intranet system is shown in Figure 1.

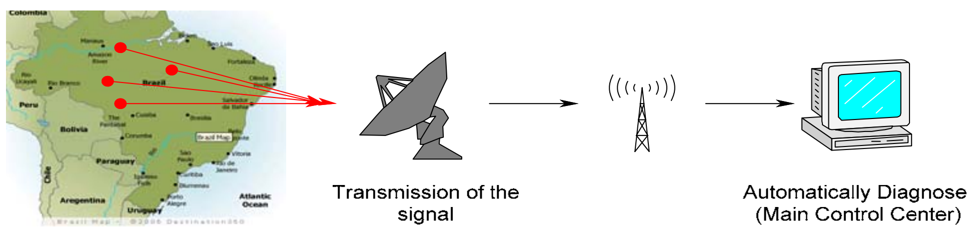

Figure 1: Remote Transmission of the Data from Small Plants to Main Control Center

Condition monitoring is commonly used to qualify and quantify the equipment's health. There are some parameters that can be analyzed to estimate the health and condition of equipment, such as oil analysis, although the parameter base used to detect the fault in this article is vibration. There are many international standards used in the diagnosis of faults. Some rules are used to quantify the possible fault, such as the severity vibration levels. There are also other rules used to qualify faults, such as Fast Fourier Transform (FFT), orbit diagram, demodulation, and others.

A special spectrum has been developed with the ability to quantify and qualify the real health condition of rotating machinery, but the principal aim is to use this data in a neural network responsible for the automatic health diagnosis of this equipment. The bandwidths will be displayed on the axis of abscissa, which is relative to the frequencies, and the amplitude relative to each band is the value referring to the vibration severity values calculated for each target band and displayed on the axis of ordinate. In this way, it is possible to convert several numbers of signal dots (more than 256 dots), which exist in FFT signals, to a few dots (less than 12 dots); using this technique, the implementation of a neural network becomes possible. The numerical results and automatic diagnosis can be transmitted by an intranet system to a central operation, and decisions can be made by a small group of experts. This technique is totally customized and can be applied to different rotating machineries with reliability. By joining this new technique with other classical techniques previously mentioned, it has been possible to build a software model that can be used effectively for maintenance management and production.

Maintenance and Management of Maintenance to the Effectiveness of the Production

Throughout the years, the importance of the maintenance function and, therefore, maintenance management has grown [6]. The quality of maintenance is directly related to reliability and availability of equipment and quality of the products. Currently, the maintenance management complements the management of production, optimizing the profits of the production and maintenance schedule, as well as the life of equipment.

Knowing what is the right maintenance program for your assets is no easy task. One might believe that the more established your company has become, the more effective your maintenance program will be. Unfortunately, this is not always true. In fact, the effectiveness of your maintenance program has absolutely nothing to do with the number of years your company has been applying maintenance. For the most part, companies are doing too much maintenance too early, or too little too late, all of which have cost implications to the organization [5].

Maintenance can be defined as a set of activities performed on a system to preserve or sustain its ability to render service in an efficient manner [3]. The production can be defined as an integrated management of the flux of raw materials, labor, equipment, and vendors optimizing the productive process. As previously mentioned, it is possible to note that equipment is directly related with production management; therefore, the availability of equipment directly affects the cost production.

There are two ways of analyzing critical equipment: the maintenance point of view and the production point of view. The maintenance critical equipment is the one that has complex solutions for its problems or physical limitations for corrective action. The critical equipment production point of view is the one that has an important chain connected to it, and if this equipment should suffer a breakdown, all of production will be affected. This way, before applying any maintenance technique, it is important to define the critical equipment and the best maintenance plan for each one.

The maintenance management areas can be divided into the following [6]:

- Maintenance optimization models
- Maintenance techniques
- Maintenance scheduling
- Maintenance performance measurements
- Maintenance information systems
- Maintenance policies

This work has focused on three areas of maintenance management: maintenance optimization models, maintenance techniques, and maintenance information systems. The neural network is used in the optimization model to detect faults and diagnose it. In the maintenance technique, predictive maintenance using vibration has been used, and the information system is an intranet network system developed for small hydropower plants. The other management techniques should be optimized following application of the former three.

Three precautions should be taken by the application of predictive maintenance [7]:

- The high cost of restoring equipment to an operable condition in a crisis situation
- The secondary damage and safety/health hazards inflicted by the failure
- The penalty associated with the loss of production

It is common for companies to experience a steady increase of maintenance costs associated with the upgrade of the production equipment and automation level, as in the research of Tu et al. [4]. The breakdowns in this type of equipment result in high production loss. It is the same for hydropower plants. The control and automation of these machines brings increased costs in maintenance, and the lack of planning for faults also increases the cost.

The application of predictive techniques in industry is becoming more usual. The competitive prices of equipment and interface hardware-software-instrumentation during the 1990s popularized the predictive methods using vibration. This type of maintenance has been used often due to the availability and success of preventative measurements for rotating machinery, which help to prevent the faults and estimate the remaining time prior to a catastrophic breakdown.

Overview of Neural Network Used in Fault Detection and Diagnostic Applications and Expert Systems

Neural networks (NN) are adaptive data processing systems that learn from examples in supervised mode or discover the intrinsic structure of the data in an unsupervised mode. In recent years, they have emerged as a practical technology with successful applications in pattern recognition and function approximation [9]. This technique has been implemented with success in condition monitoring using vibration techniques, and in this way, the NNs can be used to both detect and diagnose faults.

Basically, the artificial NNs are structured by mathematical elements denoted as neurons. The neurons receive the input signal (x) multiplied by weight (w), as shown in Figure 2. These inputs are summated, and after that, transfer functions, which are used in the treatment of signals and its output signal, can be obtained.

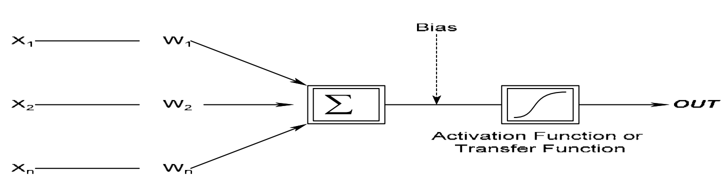

Figure 2: Basic Scheme of Neural Network

Diagnostic methods are generally divided into two strategies: model-based methods and feature-based methods. Feature-based methods involve pattern recognition techniques to distinguish between different patterns of features that are associated with different conditions. Model-based diagnostics (and feature-based fault trend assessment) are based on function approximation to relate the measured response to the underlying model [9].

This work has used a feature-based model for detecting faults in turbo-machines. In reference [9], the author has divided the feature-based monitoring into the following:

- Feature extraction: A critical initial step where the features of signals are used to input the identification faults.
- Fault detection: The NN detects two conditions, normal or abnormal.
- Fault identification: Equipment has a number of possible faults. It is possible to train one NN to detect each fault.
- Fault assessment: In this step, it is possible to predict or detect early faults.

The NNs have been applied in different manners. In references [10] and [15], the NN was used to detect faults in bearings. The first one designed two types of NNs (responsible for estimating the life of bearings using an input parameter), seven amplitudes correlation with defect frequency, and its six harmonics. Reference [15] used a simple back propagation algorithm to detect faults in ball-bearings but not to diagnose them. Statistical control charts were used for both NNs to detect and diagnose faults [11]. Also, the work used two different NN architectures: multi-layer perceptron network and radial basis function network. Both architectures were trained with output data deriving from the outcome of statistic charts. Reference [12] used the outcome from the wavelets transform signal to train the NN and diagnose the fault in an automotive gearbox. Bearings were used for 10 of the most dominant fault signals, being 10 points relative to wavelet numbers, and the other 10 correlates to amplitudes. Reference [14] applied the method of higher-order statistics (HOS), where the outcome from it is used with input data of NNs, and as a result, the rotation pump's fault could be identified. Reference [15] developed a kind of intelligent predictive decision support system for condition-based maintenance, based on the recurrent NN applied in the critical equipment of a power plant (planetary gear).

It was noted that there are two ways for the implementation of NNs: 1) to develop the ideal architecture to detect and/or diagnose faults and 2) to create good input data that is representative of the health condition of the equipment. It is also possible to use both of these implementations. This work has developed a special NN architecture with different transfer functions and numbers of layers, as well as the special data for both training the NN and the support of management decisions. The NN architecture and the new technique will be discussed in detail in the next two sections.

The Technique – Frequency Pre-defined Bands

To qualify and quantify the health of machinery, a new method has been developed. The principal characteristic is to prepare good data that will be used in a NN responsible for automatically detecting and diagnosing faults.

This technique is used to calculate the severity vibration of frequency bands totally customized by the user and, in this way, create a spectrum of frequencies versus severity vibration levels.

The severity vibration is calculated in the time domain, which avoids the problems with the resolution of power spectrum used in its calculation in the frequency domain. First, the user defines the bands of interest that should be used in analysis. Each band should be representative of fundamental frequencies of equipment, such as a rotating frequency and its harmonic frequencies. The band length is not limited, and the user can define the agreement of his applications (large or small frequency bands). This is possible because the severity bands are calculated by editing the FFT.

The motive to use edited signals instead of filters is because of the problems that can occur by the application of non-ideal filters. It is common knowledge that the filters do not immediately cut the bands of the signal [8]. The turbo machinery used in these small plants also possesses small main frequencies, where the rotating frequency value and its harmonics are close together. Because of this fact, it makes the use of filters complicated. The small bandwidth directly affects the results when the filter is applied because part of the amplitude enclosed inside this band will cut off important parts of the signal. This is illustrated in Figure 3. The value of the severity vibration correlation of this band would be incorrect, and it would not be possible to quantify the vibration level value of bands.

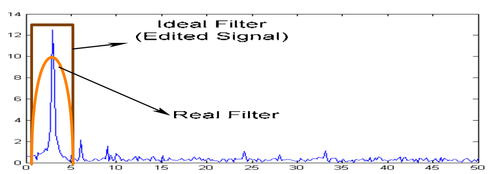

Figure 3: Cut Frequency by Use of the Filter and Edited Signal

To describe the implementation of this solution, the signal in the time domain is transformed in the frequency domain using the algorithm FFT. After that, the amplitudes outside that frequency band defined by the user are set equally to zero, and it is possible to obtain only the amplitude correlations within the band of interest. After this step, the inverse of FFT is applied, converting the edited signal in the frequency domain to the edited signal in the time domain. Finally, by using the edited signal in the time domain, it is possible to calculate the severity vibration of each band defined by the user. Figure 4 shows the application of this process.

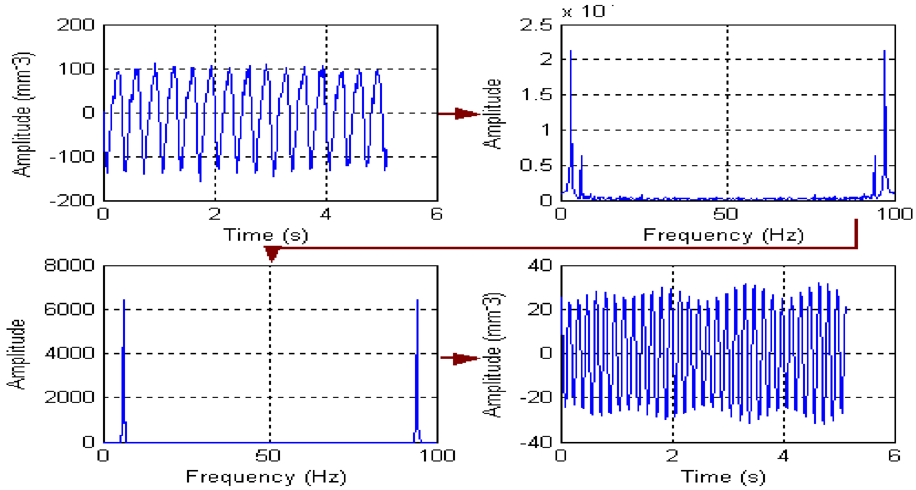

Figure 4: Procedure of Calculation of the Severity Vibration of the One Frequency Band (Second Harmonic)

The severity vibrations that can be calculated are RMS values and the relative displacement between shafts-housing-bearings (peak-to-peak maximum value). The calculation of RMS or displacement depends on the type of sensor used in the measurement. If the sensor used is accelerometer, the RMS value is obtained; on the other hand, if an eddy current transducer is used, the severity vibration value calculated becomes displaced. Equations (1) and (2) are used to obtain the RMS and the displacement severity vibration, respectively [8].

$$V_{RMS} = \sqrt{\frac{1}{T} \cdot \int_0^T \left(v(t)\right)^2 \cdot dt} \qquad (1)$$

where V_{RMS} is the root mean square, v is the measured signal, and T is the signal period.

$$S(t) = \sqrt{[S_A(t)]^2 + [S_B(t)]^2} \qquad (2)$$

where S is the instant maximum amplitude, S_A is the signal of the first inductive sensor to the axle, and S_B is the signal of the second inductive sensor perpendicular to the first one, toward the axle rotation.

The instrumentation, as well as the setup of sensors on the machine, are based in standards ISO [16], [17], and [18], as well as reference [8].

The length of the data outcome of the implementation of the band spectrum is very short if it is compared with a normal signal by the application of FFT. The FFT dots are multiplied by 256; therefore, there are so many dots in a classic FFT, it becomes impossible to use the results in the training of NNs. The opposite occurs with the spectrum of frequency pre-defined bands (FPDBs). The maximum dots possible by FPDB algorithm are 12, and its outcome can be used as an input data in a NN system.

By using this spectrum, it becomes possible to observe the severity levels of each band. Trip value and alarm limits can be defined by the user for each band.

Neural Network Architecture and FPDB Technique Used in Training

Before the FPDBs' data can be used by NN, it is necessary to normalize them, and the outcome data needs to pass through the preprocessor. In the preprocessor, all of the vibration severities are divided by severity values relative to the rotating frequency band. In this way, the severity vibration of the bandwidth will always be relative to the rotating frequency, whereas the other bands will be a percentage of this band. Such a procedure results in low values that render speed and reliability to the network.

In this way, it is possible to train the NN. This article will use only misalignment fault. For the misalignment, the amplitude of the rotation frequency's harmonics increases where the predominant frequency is the second harmonic [8, 19, 20].

Three input data have been used to train NNs. One identifies equipment in good condition, and the two others detect the faults, which in this case are misalignment and unbalance.

The implemented NN has four layers in which the transfer functions applied to each one follow this sequence: hyperbolic tangent sigmoid transfer function, hyperbolic tangent sigmoid transfer function, linear transfer function, and linear transfer function. Neuron numbers per layer are equal to 3, 15, 15, and 1.

The FPDB signature is used to train a NN to detect faults. Such a spectral signature has proven to be much more effective than the standard spectrum obtained by FFT for its ability to reduce data entering the NN. The technique presented herein allows faults to be clearly identified using, at most, 12 band values; hence, 12 values relative to the bands' central frequencies and to their respective vibration severity, countering the FFT spectrum that generates from 512 to 4,096 dots. This makes it slow and difficult to use in NNs for the automatic detection of possible faults.

The Software Model

The parameters monitoring and estimate procedure has been developed in the MatLab environment, which was chosen for its handy tool box and workability. Moreover, its low-level C++ language allows compilation and conversion into a portable, easy-to-run file.

The software has been divided into four different areas called environments: file environment, analysis environment, configuration environment, and monitoring environment.

The main goal of the file environment is to read an ASCII-extent data file related to a signal coming from specific equipment that needs to be monitored. Each signal from the various tuned channels is featured through a column vector. The sample data rate and the number of samples per pack (NSP) will be read straight from the ASCII file. The signal pack number (SPN) will be estimated by the relationship between the sample-per-pack total number from the acquisition (SPTNA) and the number of points per pack (NDP).

After this, the signal downloading analysis environment can be used. In this environment, it is possible to find some classical tools in PDM, such as FFT, demodulation, orbit diagram, time synchronous average, severity vibration levels (RMS and displacement), and filters (see Figure 7.) In this environment, the experts should analyze and diagnose the condition of the machines to determine the main frequencies and other parameters that need to be analyzed before the configuration of FPDBs.

After analyzing and determining the condition of the equipment, it is possible to define the bands that should be used for building the FPDBs. For each existent channel, the user can be defined up to 12 frequency bands. The user should be able to choose bands representative of the condition of the machinery as: rotating frequency and its harmonics, mesh gears frequency and its lateral bands, and other frequencies considered important to the analysis. In this environment, the global alarm and emergency value should be defined, along with the alarm and emergency value for each band. This environment is shown in Figure 5.

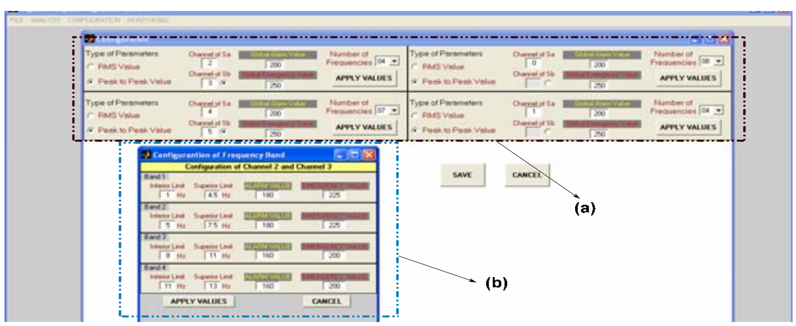

Figure 5: Windows from Configuration Environment: (a) Definition of Severity Vibration, Global Alarm and Emergency Value, and Number of Bands; (b) Definition of Bandwidth, and Band Alarm and Emergency Value

After this step, it is possible to apply the FPDBs technique, whose solution has been described previously, and to establish the real health condition of equipment by the use of NN. The visual outcome from the application of monitoring the environment is shown in Figure 8.

In the monitoring environment, there is a trend graphic tool that is used to plot a tendency graph and estimate the remaining life of the equipment.

By observing the vibration severity tracks defined in the rules, around 3dB severity measurement variation (equation 3) is thought to be a significant change on the vibration severity value, and it shows that the equipment is migrating to a higher severity level [8].

$$20 \cdot \log_{10}\left(\frac{X_i}{X_{i-1}}\right) \geq 3 \qquad (3)$$

where X_i is the current severity value, and X_{i-1} is the severity value obtained in the previous inspection.

A dynamic alarm comes on when there is a 3dB increase in the vibration severity value over the acquisition period defined by an expert or, in a more severe case, when such a change takes place between two consecutive acquisitions, warning that the equipment is rapidly deteriorating. Through FPDBs, such an analysis may be carried out in detail, using the band severity value variation along with the equipment mobile components and the measurement-related global value. In this way, it is possible to apply four types of alarms:

- Dynamic alarm (3dB rule)
- Global alarm and emergency (based in standard rules)
- Band alarm and emergency
- NN diagnosis

In this way, it is possible to prevent and to predict a catastrophic fault. The focus of this work is in the management of maintenance improving production. Many authors, such as those in references [4] and [5], have developed techniques and software aimed solely at production costs but with different points of view, as highlighted in this work. By using the case example and this software model, which will be explained in the next section, it is possible to improve the maintenance without resulting in a loss of production.

Application and Results in Real Cases

To demonstrate the described technique and the software model, signals obtained from the monitoring of a small hydropower plant called “BURITI” in Brazil have been used; the machines are kaplan-like, with five rotor blades and 16 mobile directional blades. Its nominal rotation is 327.27 rpm (5.45Hz). The generator is a 22-pole synchronous-like, and its nominal rotation is 327.27 rpm (5.45Hz). The turbine shaft is attached in front of the directional blades by a TGHB (turbine guide house-bearing), and between the generator and concrete structure is a shaft that is supported by a trust and journal combined house-bearing (TJHB). The focus of this measurement is the turbine of the small plant; because of this, the other elements, such as the generator and its components, are not described. The illustration of the machine and instrumentation is shown in Figure 6.

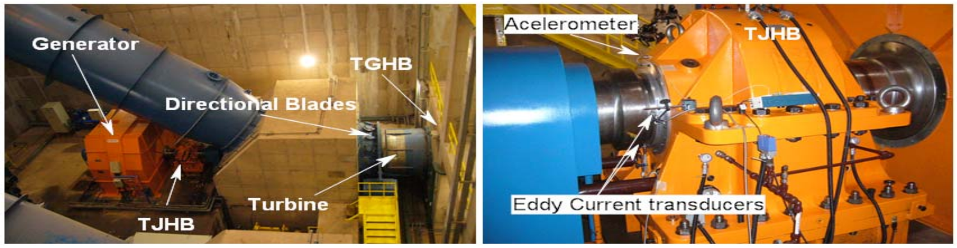

Figure 6: Illustration of the Machine and Setup of the Instrumentation

The setup of the instrumentation was used following the standards ISO [16, 17, 18] and reference [8]. The global severity vibration levels are based on these same standards and reference. For this machine, the global severity vibration for good conditions (level A) is up to 78µm for peak-to-peak value (PP) and up to 1.6mm/s for RMS value. Four frequency bands were set up: first band (5.3Hz to 5.6Hz), second band (10.7Hz to 11.1Hz), third band (16.1Hz to 21.4Hz), and fourth band (16.7Hz to 22.1Hz). The alarm and emergency value (trip) for each band are: first band (116µm and 150µm), second band (43.5µm and 56.5µm), third band (29µm and 38µm), and fourth band (14.5µm and 19µm). The FFT of the signal from the machine with a light misalignment is shown in Figure 7.

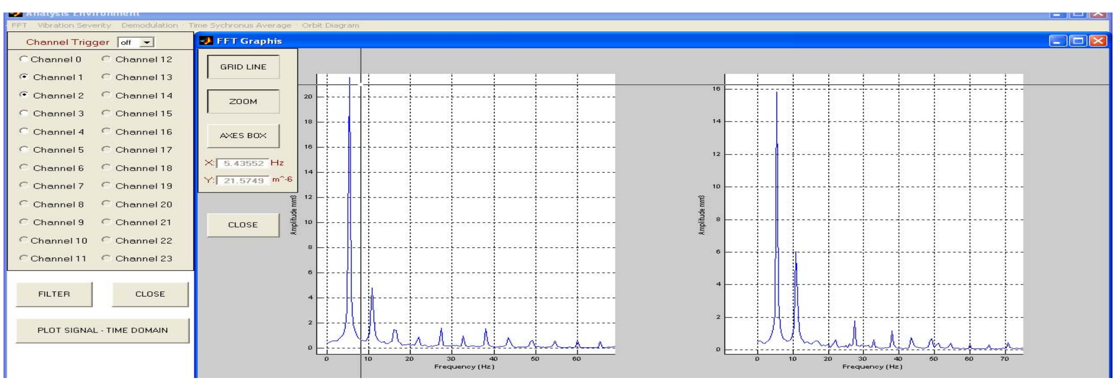

Figure 7: The Global Viewing of Analysis Environment Window – The FFT of the Signal in Case 2 Was Applied as an Example

The FPDBs have been applied for this signal. The visual outcome is shown in Figure 8.

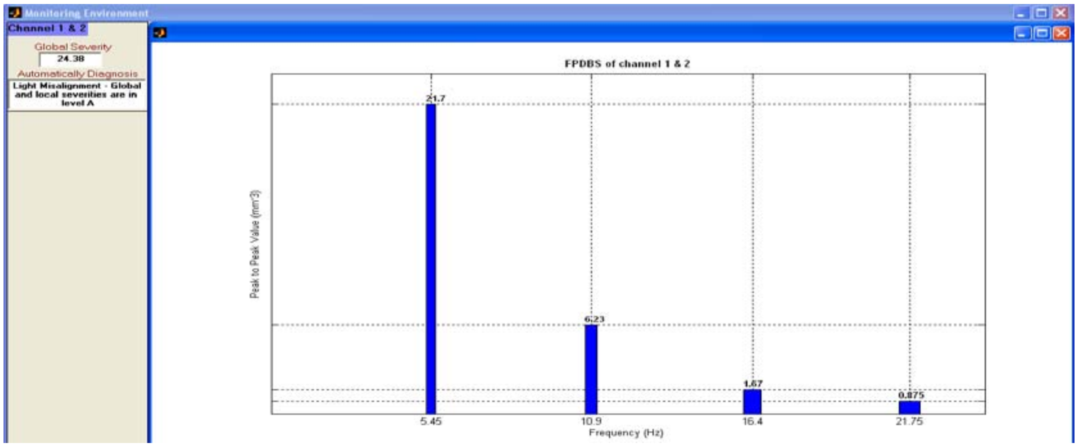

Figure 8: The Global Window of the Monitoring Environment, FPBDs Graph and Automatically Diagnose (case 2)

This signal spectral signature has been used to train the NN, which tells whether or not the equipment is in good condition, respectively, 1.0 or a different out-flow.

If a comparison is made between FPDBs and the classical spectrum (Figure 8), it is possible to notice that the classical spectrum has more points (about 512) and noise. It has been trained a NN using input data from this classical spectrum, but the result was not acceptable to qualify the fault. Another point of this new data reduction technique is the possibility of quantification of faults (bands severity levels) that do not occur with the classical spectrum (fault is qualified by an expert.)

The light and hard misalignment fault has been analyzed in this case study. It has been trained using three different NNs to detect every case. The first case (case 1) is a correlation with the machine in a good operating condition, and it is used as a reference to detect the other two faults. Cases 2 and 3 represent the light and hard misalignment. In the good condition, the amplitude of the bandwidth harmonics is less than 3 percent of the amplitude of the bandwidth of the rotational frequency. When considering a light misalignment, the signal when the amplitude of the bandwidth harmonics are 10 to 30 percent of the amplitude of the bandwidth of a rotational frequency. In comparison, when considering a hard misalignment, the signals when the amplitude of the bandwidth harmonics are 30 percent up to 55 percent of the amplitude of the bandwidth of the rotational frequency. If the outcome from NN of case 1 is a different value than one, the FPDBs are transferred to other NNs to detect what type of misalignment is occurring. Table 1 shows the global and local vibration severity values.

Table 1: Global and Local Severities of the Turbine

	Global (PP)	Global RMS	Band 1 (PP)	Band 2 (PP)	Band 3 (PP)	Band 4 (PP)
Case 1	21.21µm	-	20µm	0.49µm	0.33µm	0.17µm
Case 2	24.38µm	0.68mm/s	22.4µm	7.19µm	1.94µm	0.92µm

Case 3	18.83µm	1.4mm/s	16.3µm	6.33µm	1.48µm	2.48µm

For such training, FPDBs were simulated with the standard signatures for these kinds of faults. For such a spectrum, the NN must have a 1.0 out-flow. The initial network has offered 1.00 out-flow, with a good signal condition to the turbine showing an absence of faults. When light and hard misalignment signals were used, the NN referring to a non-defective signal resulted in the following values for turbine: 0.46 and 0.48. In this case, the NN corresponding to both light and hard misalignment showed, respectively, NN2 (1.00 and 0.79) and NN3 (0.34 and 1.00). Table 2 shows the outcomes from each NN for each case.

Table 2: Outcomes from NNs of Each Case

	Outcome NN1	**Outcome NN2**	**Outcome NN3**	**Automatically Diagnose**
Case 1	***1.00***	-	-	Good Conditions. Global and local severities are in level A.
Case 2	0.46	***1.00***	0.79	Light misalignment detected. Global and local severities are in level A.
Case 3	0.48	0.34	***1.00***	Hard misalignment detected. Global and local severities are in level A.

It can be noted which severity levels are in good condition for continued operation, but the diagnoses of NNs for cases 2 and 3 detect the misalignment fault. This is correct because for the machine to continue the operation in case 3, the premature fault will occur. The inverse case could happen, for instance, if the NN does not detect the fault, but the global and local levels increase, resulting in another type of alarm.

Conclusion

This work can contribute to the management system of maintenance and schedule in preventing faults via the use of predictive measures in industries of any size, hydroelectric power plants, and others.

The main interest of this work is to illustrate the efficient application of data from the FPDBs technique used as input data in NN, providing reliable and quick diagnosis (detection of faults). The procedure introduced herein has shown to be adequate for monitoring tele-operated industrial plants, as is the case of small hydropower plants, which encouraged this study. Installed on the automatic operation system, the device runs a diagnosis by means of artificial intelligence tools and sends alarms and emergency signals according to the need. It simultaneously allows the operator to, at any time, remotely visualize the indications and vibration conditions of machinery in relation to the deterioration or progression of faults, while being able to make his or her own decisions or send these results to experts.

Another interesting point is the configuration of the system, that is, a specific customization of the equipment. This configuration banishes the necessity for the need of experts and specific acquisition equipment for each machine. The experts could configure the monitoring for different machines using one piece of software. With the configuration defined by an expert, the acquisition and data analysis could be done by technicians for the values and spectral configuration correlations, with possible faults for emergency (trip) and alarms that were set by an expert.

Other parameters of predictive maintenance could be added to this software, such as oil analyses and temperature of housing bearings, increasing the kinds of diagnosis that could be applied.

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