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A DSP-Based FFT-Analyzer for the Fault Diagnosis of Rotating Machine Based on Vibration Analysis

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***Abstract*—A DSP-based measurement system dedicated to the vibration analysis on rotating machines was designed and realized. Vibration signals are on-line acquired and processed to obtain a continuous monitoring of the machine status. In case of a fault, the system is capable of isolating the fault with a high reliability. The paper describes in detail the approach followed to built up fault and unfault models together with the chosen hardware and software solutions. A number of tests carried out on small-size three-phase asynchronous motors highlight the excellent promptness in detecting faults, low false alarm rate, and very good diagnostic performance.**

***Index Terms*—DSP, fault diagnosis, frequency domain analysis, rotating machines, vibration analysis.**

I. Introduction

In the field of rotating machine monitoring and on-line diagnosis, the analysis of the vibration is very effective [1]–[10]. In fact, each machine defect produces vibrations with distinctive characteristics that can be measured and compared with reference ones in order to perform the fault detection and diagnosis.

Both time-domain and frequency-domain methods can be used to analyze vibration signals. The time-domain approaches, even though providing insight into the physical nature of the vibrations, become practically impossible in the presence of multi-tone vibration signals. Vice versa frequency-domain approaches, allowing both the amplitude and phase spectrum to be identified, are more useful for the vibration analysis [11]–[13]. The frequency analysis of the vibration signal followed by further processing of the resulting spectrum allows precise diagnosis information to be obtained [14], [15]. Among the methods using frequency analysis there are bearing defect frequency analysis methods, high-frequency shock pulse and friction force methods, and enveloped spectrum methods [14].

The most frequently used instrument for vibration analysis in the frequency domain is the dynamic signal analyzer (DSA) [16], which is able to evaluate how the spectrum changes in time and consequently supports the description of the time-limited event. There are a wide variety of DSAs on the market (handheld, benchtop instruments, computer-controlled systems), and the choice of the most appropriate for the vibration analysis has to be based on considerations about elaboration speed, display resolution, price, and portability.

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In any case, giving a correct and early alarm is one of the goals for a continuous on-line monitoring system. Consequently, an effective vibration analysis for on-line machine monitoring and diagnosis requires the following:

i) a real-time analysis, for assuring good promptness in fault detection;
ii) an optimum choice of the best measurement values (sampling frequency, number of points, and window function [17]), in order to obtain a high sensitivity and selectivity in the fault identification;
iii) dedicated diagnostic software integrated in DSA, for suitably correlating the vibration with its cause and for understanding the fault severity.

General-purpose instruments cannot satisfy all of these requirements contemporaneously. In fact

i) the spectrum visualization is very time consuming and, consequently, for most DSAs, the spectrum evaluation can not be performed in real-time;
ii) the configuration phase is not automatic, and changing the DSA set-up by a software controller is not efficient in terms of elaboration time;
iii) for on-line fault isolation, the data exchange between the DSA and the diagnostic software has to be executed efficiently, and dedicated software is, in practice, not available.

In the field of real-time high-performance frequency analyzers, the authors have already designed an intelligent FFT analyzer [18]–[20]. A configuration procedure, suitably developed, allows the instrument to automatically adapt its operating parameters on the basis of the signal spectrum. It was customized for a number of typical frequency analysis applications, such as for example, tone monitoring and detection. The use of a two-DSP parallel architecture allows 50-kHz bandwidth signals to be analyzed in real-time.

In this paper, the authors customize the intelligent FFT-Analyzer for rotating machine monitoring and diagnosis by suitably modifying the software [21], [22]. In particular, a model-based diagnostic approach was implemented [23]–[25]. It consists of a pattern matching procedure, which detects and isolates the fault by comparing the actual device model with unfault and fault ones.

In the following, the technique used for identifying unfault and fault models is reported first. Then the designed measurement system is described, detailing both its hardware and software characteristics.

Finally, the performance of the proposed apparatus is verified on a number of tests in different faulty and unfaulty operating conditions.

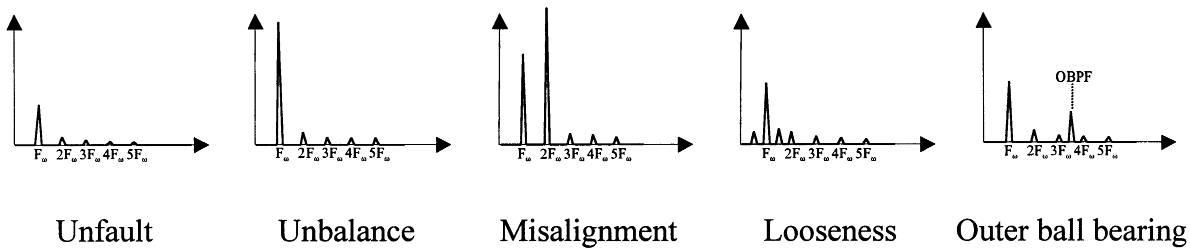


Fig. 1. Qualitative vibration spectra in unfaulty condition and in presence of some typical faults.

II. Identification of Unfault and Fault Models

A model-based diagnostic approach requires the identification of unfault and fault models. In the frequency-domain analysis of vibrations, these models can consist of suitable parameters of the vibration signal spectra.

Some studies are presented in the literature about the relation between defects and vibration characteristics in electrical machines [1]–[10].

The vibration spectrum during normal (unfault) operation is characterized by a tone located at the shaft rotating frequency, F_ω, followed by a number of harmonics whose amplitude is generally less than one-third of the F_ω amplitude (see Fig. 1). If a gear is present, at least three main additional tones appear: one at the running speed of the low-speed shaft, one at the running speed of the high-speed shaft, and another one at the gear mesh frequency. Furthermore, a number of other tones are present in the unfault signal spectrum due to vibrations of the structure where the motor is plugged on.

Every kind of mechanical failure causes a specific alteration of the spectrum with respect to the unfaulty one. In the following, some examples are given of the most common faults.

A shaft **unbalance** causes a high intensity radial vibration at F_ω, with an amplitude depending on the stiffness in the direction of analysis. The effect on the spectrum is a remarkable increase in the amplitude of the tone at F_ω.

A radial vibration at a frequency equal to $2F_\omega$ is the main effect of a **misalignment**. In this case, the tone amplitude at $2F_\omega$ usually exceeds 75% of the amplitude of the F_ω tone, and even 150% in the case of serious damage. Another symptom of a misalignment is an intense axial component of the vibration.

A mechanical **looseness** in the bearing cap or support is characterized by a large number of harmonics, and above all sub-harmonics, in the vibration spectrum, depending on the point and the direction of analysis. Other types of looseness involve the support of the whole machine; in this case, the effect is simply an increase of the F_ω tone amplitude.

An important class of problems involves the **gear** operation. This component generates a broad spectrum that extends from frequencies below F_ω up to multiples of the gear mesh frequency. The gear mesh frequency tone is generally surrounded by other lower tones located in two sidebands. Gear defects like wear, misalignment or backlash cause an alteration in the number and amplitude of these sidebands.

A **bearing** defect produces spectrum tones at frequencies depending on the geometrical parameters of the bearing and the running speed. These frequencies are the running speed, the inner and outer ball pass frequencies (IBPF and OBPF), the ball spin frequency and the train frequency. For example, a single defect in the outer race of the bearing causes an impulsive vibration each time a ball passes over the defect.

This analysis of machine vibration characteristics allows the identification of both numerical and logical model parameters. In particular, the number of tones, the amplitude of the first five harmonics of F_ω, the amplitude ratios between the second harmonic $(2F_\omega)$ and the fundamental (F_ω), and the sum of all tone amplitudes are considered as numerical parameters of the model. Some characteristic frequencies $(0.5F_\omega, 1.5F_\omega, 2.5F_\omega,$ OBPF, IBPF) are considered as logical parameters.

Of course, the values of unfaulty and faulty models have to be estimated on the basis of real measurement data. This exigency is clearly pointed out by meaningful differences between a real unfault spectrum [Fig. 2(a)] and a qualitative theoretical one (Fig. 1). This represents a troublesome problem, typical of the diagnostic system on a real apparatus, since most of the faults (e.g., defects in the inner or outer race of the ball, misalignment, mechanical looseness) are not reversible and/or impossible to be produced at desired time instants during the motor operation.

In order to overcome this problem, a specific procedure based on fault emulation was set up. It is based on a suitable processing of the real unfault signal performed by an arbitrary waveform generator. It is featured by a powerful frequency editing function that allows an easy tone addition and/or modification in order to obtain fault spectra (see Fig. 2). The use of an arbitrary waveform generator also allows the fault to be produced in any instant of the machine operation, by using test sequences composed of unfault and fault subsequences.

The correctness of the proposed emulated approach can then be verified by producing some reversible faults on the machine under test.

III. Designed Station for Vibration Analysis

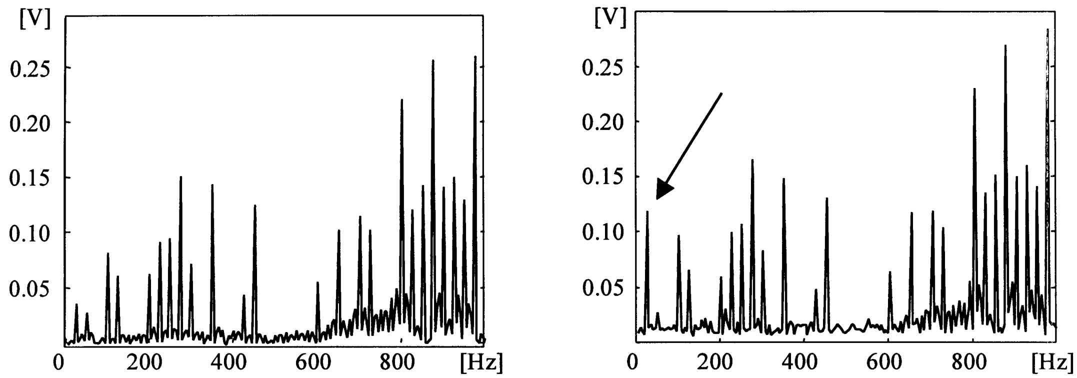
The hardware and software of the designed system were optimized for a specific class of motors, namely small-size, three-phase, two-pole pair, asynchronous motors.

Of course, this customization does not reduce the generality of the proposed system, since both hardware and software are highly reconfigurable.

A. Hardware of the DSP-Based FFT-Analyzer

A block diagram of the designed system for the fault diagnosis on a small-size electrical motor is reported in Fig. 3.

The sensing section consists of an acceleration sensor (8710A50M1 by Kistler™) characterized by low output



(a) (b)

Fig. 2. (a) Unfault spectrum and (b) the one obtained by modifying the tone at $F_\omega = 25$ Hz.

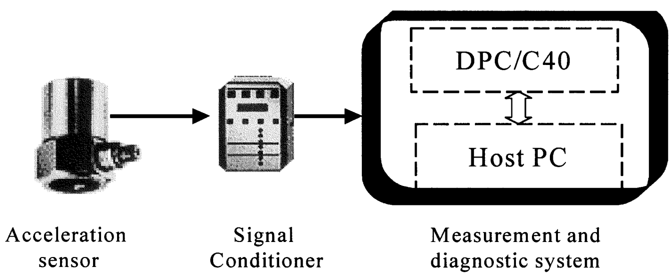


Fig. 3. Block diagram of the designed station for vibration analysis.

impedance (about 100 Ω), 6 kHz upper cut-off frequency, 1000 mV/g sensitivity, 5 g measuring range, and 51 g of mass loading. The accelerometer is magnetically mounted directly on the motor under monitoring, in order to assure an optimum coupling.

A signal conditioner with adjustable gain (5118B1 by Kistler™) is then used to adapt the sensor output to the input range of the acquisition and elaboration section.

As previously said, the acquisition and elaboration section is the same used for the intelligent FFT-Analyzer described in detail in [18]–[20]. It is based on a PC-bus compatible carrier board, the DPC/C40 by Loughborough Sound Images™ with two concurrent DSPs and an on-board data acquisition system (Analog Daughter Module, ADM, by Burr-Brown™). The two mounted DSPs are the TMS320C40 by Texas Instruments™; they use a floating-point numerical representation with 32 bits, and work at 40 MHz. The DSPs are in a Master/Slave configuration (only the Master DSP can directly access the board resources), and communicate by using six serial ports. The ADM is featured by two Delta-Sigma ADCs and two DACs with 16-bit resolution, 200 kHz maximum sampling frequency, +3 V full-scale, and 20 kΩ input impedance. The ADM communicates with the Master DSP by a serial nonstandard interface (AMELIA).

The data transfer between the Master DSP and the host PC is carried out by using a shared 4 K × 32-bit memory.

B. The Software

Dedicated software was developed to feature the previously described measurement system with monitoring and diagnostic

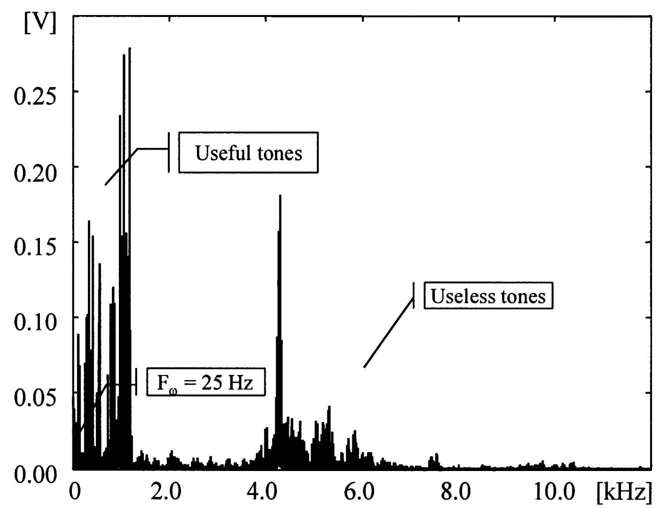


Fig. 4. Unfault vibration spectrum.

capabilities. It can be subdivided into three main procedures corresponding to the three steps needed to achieve a model-based on-line monitoring and diagnosis: i) signal processing for actual model estimation, ii) fault detection, and iii) fault diagnosis.

All of these procedures have been implemented on the DSPs in order to optimize the response time.

The signal processing: The signal processing software, executed in parallel by the two DSPs, analyzes the vibration signal in the frequency domain, and evaluates the characteristics of its spectrum, chosen for representing the actual model of the motor under test.

The software for the on-line spectrum evaluation is an optimization of the intelligent FFT-Analyzer measurement procedure [18]–[20], on the basis of the knowledge of the unfault vibration spectrum and on the expected fault ones (see Section II).

The measured unfault spectrum (see Fig. 4) has tones up to 8 kHz, and consequently the sampling frequency has to be fixed at 16 kHz to avoid aliasing. Theoretical analysis reported in the literature applied to the motor under test suggests that the considered faults give rise to additional meaningful tones not higher than 1 kHz. Thus, to improve the frequency resolution, the acquired signal is filtered (30th order FIR filter with 1.1 kHz cut-off frequency) and decimated ($\text{decimation factor} = 4$). A dedicated algorithm performs the two operations in a single

TABLE I
MAXIMUM ELABORATION TIMES FOR THE DIFFERENT ALGORITHMS OF THE SIGNAL PROCESSING PROCEDURE

Algorithm	Filtering + Decimation	Windowing + FFT	Tone detection + interpolation + model parameter estimation
Elaboration time	70 ms	11 ms	3 ms

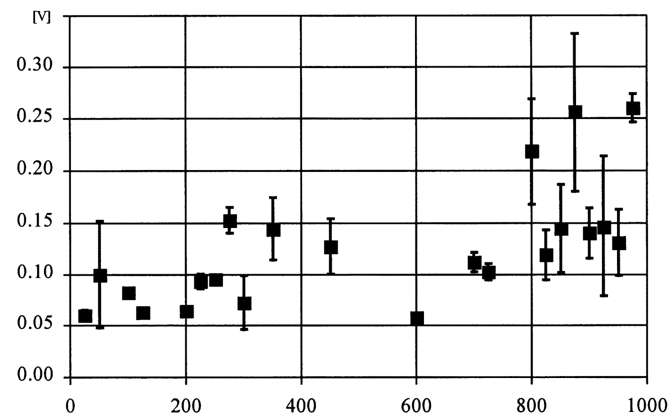


Fig. 5. Values of tones measured in unfaulty conditions.

step [18], allowing a meaningful reduction of the computational load. The so-obtained sample sequence (2048 points) is windowed, and the FFT is evaluated. The amplitude spectrum is analyzed in order to detect the signal tones [18]; for each one of these, the amplitude and frequency are estimates interpolating the FFT samples [26], [27].

Finally, the actual motor model is estimated in terms of both numerical and logical parameters. Table I reports the maximum elaboration times of each step of the signal-processing procedure. These times do not allow a diagnostic activity to be carried out at each sampling, but they are in perfect agreement with the timing usually expected for the monitoring of this kind of apparatus working at industrial frequency.

The fault detection: Each time the signal processing procedure is completed, the chosen characteristics of the measured spectrum are compared with the reference unfault ones, with the aim of detecting the presence of faults. The high variability in successive measurements, carried out in different motor operating conditions, suggests the use of a statistical approach for identifying the reference vibration spectrum model parameters. In particular, the vibration spectrum in the absence of faults was calculated 20 times. Fig. 5 reports the mean values and the variability of each tone amplitude, estimated as three times the standard deviation. As for the frequency variations, they prove to be always contained within ± 0.5 Hz around the measured mean values.

A weighted squared sum of the difference between actual and unfault numerical parameters is continuously evaluated and compared with a suitable threshold. Checks on the logical parameters are performed too. In order to avoid false alarms, a fault is highlighted only when the threshold is overcome, or a check is positive in two subsequent spectrum analyzes.

The DSP Master executes this fault detection procedure, taking about 0.01 ms.

The fault diagnosis: A correct fault diagnosis requires reasoning on spectrum parameters referring to a complete fault time interval. Consequently, the fault isolation procedure is activated on the signal processing results obtained after the fault detection.

A rule-based diagnostic procedure was directly implemented on the Master DSP rather than on the PC, in order to obtain better time performance.

First the checks on the logical parameters are performed, allowing the related faults to be highlighted or discarded. For an example, a defect in the outer race of the ball bearing gives rise to a tone at OBPF. In these cases, the diagnostic procedure stops (like for "demon fires" in an Expert System), and only the corresponding fault is given with a certainty factor equal to one. Table II reports the kind of faults that are identified by these demons with the corresponding characteristic frequency.

If no one of these conditions is verified, the procedure goes on applying rules focused on increasing the certainty factor of other possible faults. In particular, for each fault the certainty factor is increased as a function of the distances between the actual model and its fault model. The certainty factors were tuned in the set-up phase in order to optimize the diagnostic performance.

The output of this procedure is a list of probable faults, each with its certainty factor. A fault is considered as "probable" if its certainty factor is greater than a suitable threshold (0.5) [28], [29].

This diagnostic list is also passed by the Master DSP to the PC via Shared Memory.

The DSP Master executes this fault diagnosis procedure, taking about 0.02 ms.

IV. EXPERIMENTAL EVALUATION OF THE SYSTEM DIAGNOSTIC PERFORMANCE

As for the performance evaluation, in terms of diagnostic capabilities and response time, of the designed instrument, numerous experimental tests using real and emulated signals are carried out.

The false alarm rate is evaluated by running the diagnostic procedure during the motor normal operation in different working conditions. No false alarm occurs in 20 tests lasting 30 min each.

The instrument was then tested on emulated signal sequences composed of the unfault vibration signal followed by fault ones. For each fault, different fault signals are created, changing the

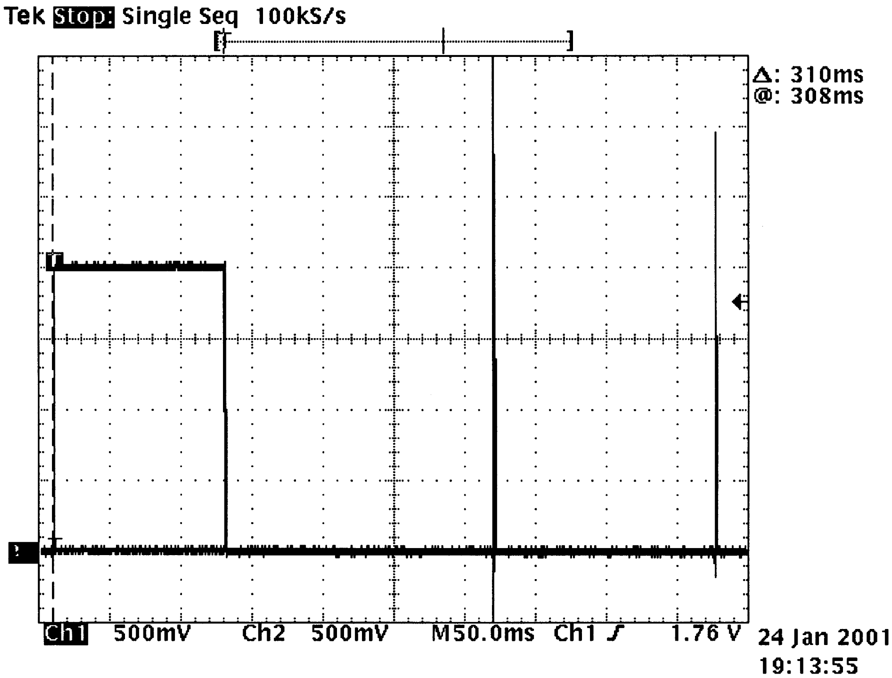


Fig. 6. Example of response time measurement.

TABLE II
FAULTS DETECTED BY DEMONS, THEIR CHARACTERISTIC FREQUENCIES AND THE REASONS OF THEIR VALUES

Fault	Frequencies	Reason
Looseness	12.5 Hz-37.5 Hz	(0.5-1.5) F_{ω}
Outer	127.5 Hz	Outer ball bearing dimension
Inner	112.5 Hz	Inner ball bearing dimension

TABLE III
DIAGNOSTIC PERFORMANCE OF THE DESIGNED STATION

Kind of fault	CD %	MD %	CL %	QL %	IL %	ML %
Unbalance	99.5	0.5	99.5	0.5	0.0	0.0
Dynamic Unbalance	100.0	0.0	99.5	0.5	0.0	0.0
Angular Misalignment	99.5	0.5	99.0	0.5	0.0	0.5
Parallel Misalignment	99.5	0.5	99.0	0.0	0.0	1.0
Inner ball bearing	100.0	0.0	100.0	0.0	0.0	0.0
Outer ball bearing	100.0	0.0	99.5	0.0	0.0	0.5
Looseness	98.5	1.5	99.0	0.0	0.0	1.0

frequency and the amplitude of the tones, in the previously presented range in order to take into account the normal variability of the signal spectrum. For each fault, different sequences were built up by changing the fault instant, in order to take into account the random nature of the fault instant. Two hundred tests for each fault were carried out, and the obtained diagnostic results are detailed in Table III.

The performances of the fault detection procedure are expressed in terms of correct (**CD**) and missed detection (**MD**) percentage.

For the diagnostic procedure, some classes are identified, and the percentages of each class are reported:

CL—Correct location. The actual fault is in the diagnostic list with the higher certainty factor.

QL—Quasicorrect location. The actual fault is in the diagnostic list but not with the higher certainty factor.

IL—Incorrect location. The actual fault is not in the diagnostic list.

ML—Missed location. The diagnostic list is empty.

As far as the response time is concerned, delays between the fault detection and diagnosis and the fault instant are evaluated as follows. The arbitrary signal generator can provide an additional signal (marker), with only two amplitude levels (0–2 V), that can be synchronized with the generation of a specific sample. The fault instant can be exactly identified by synchronizing the marker with the beginning of the fault signal in the sequence. On the other hand, one ADM D/A converter can be used for highlighting the instants in which the DSP-based system reaches the detection and the diagnosis. In particular, a 3-V voltage pulse is generated as soon as a fault is detected and when the diagnostic process is ended. These two signals are displayed on a digital oscilloscope (Tektronix TDS 520D, 500 MHz bandwidth, four input single-ended channels), allowing the response time of both fault detection and fault diagnosis to be measured (see Fig. 6). Of course, the measured response times are not constant since they depend on a number of factors, such as the kind of fault (magnitude of the vibration change) and the relationship between the fault instant and the signal processing procedure.

A mean delay of 300 ms for the fault detection and of 470 ms for the diagnosis is measured. A set of unbalance faults was also produced on the motor in order to check the proposed fault model as well as the emulated approach.

Unbalance faults are suitably realized by applying weights to the shaft of the machine. Different values of the weights (77.5 g, 65 g, and a couple of 40 g weights) are placed on the shaft at different angles, in order to test the system for different faults of this class. Diagnostic results in optimum agreement with the one obtained by the emulation approach were obtained.

V. Conclusion

In this paper, a DSP-based architecture for vibration analysis is described. It allows machine monitoring to be carried out on-line, with a consequent increase in the system and in environmental safety.

The use of parametric unfault and fault models, estimated by extracting specific characteristics in the vibration spectrum, allows dealing with data strongly corrupted by noise, such as those typical in a real application.

The integration of the traditional signal-processing algorithm with rule-based reasoning for fault detection and isolation presents many advantages, especially concerning the diagnostic performance of the system, with correct diagnosis in more than 99% of the situations.

The emulation-based method used to estimate the vibration signal in the faulty condition proves to be very effective and can be easily extended to numerous application fields.

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