A Neurofuzzy Application for AC Motor Drives Monitoring System

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***Abstract*—Currently industrial applications require suitable monitoring systems able to identify any decrease in efficiency resulting in economic losses. This paper shows that the information coming from a general purpose monitoring system can be usefully exploited to realize a sensorless instrument for the monitoring of an ac motor drive, and can be fed to a diagnostic tool for providing useful risk coefficients. The method is based on digital processing of the line signals acquired by means of a virtual instrument. The employed wavelet algorithms have been implemented within a Matlab environment, and risk coefficients are generated by means of suitable neurofuzzy algorithms.**

***Index Terms*—Neurofuzzy, virtual instruments, virtual test bed.**

I. Introduction

A monitoring system can be defined as a set of devices, procedures, and diagnostic tools to track every single step of a process. Every industrial application requires a suitable monitoring system for its processes in order to identify any decrease in efficiency resulting in economic losses. Early detection of the deviation of the operating conditions from optimality may avoid subsequent faults, or even failures. In a previous paper [1] the authors showed that the generic information from an electric power measurement system, which monitors the power consumption of an electric load, can be usefully exploited for sensorless monitoring an ac motor drive. Postprocessing of data provides useful information about the status of the drive. The capability of digital signal processing (DSP)-based instruments to execute complex postprocessing algorithms in real time makes the implementation of continuous monitoring functions possible. As a result, dedicated remote monitoring of a set of electric loads in a large plant is in turn feasible [2].

The option of combining diagnostic and monitoring operations on an ac motor drive without using dedicated sensors cannot offer diagnosis as reliable as that provided by totally customized systems [3]. Nevertheless, useful diagnostic indications can be obtained by this low-cost extension of the monitoring activity, and the reliability of the obtained indications can be significantly increased if the combination of advanced transforms, such as wavelet transforms, and fuzzy computation is used [4].

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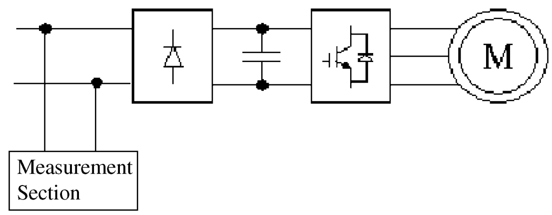

Fig. 1. Scheme of the system under test.

A fuzzy index is introduced as a risk coefficient, giving the user the likelihood of being in a fault condition.

II. Monitoring and Diagnostic Tools

This paper describes the design of a diagnostic tool for an ac drive. Having in mind the recent trend toward more and more integrated systems, where the drive can be considered as a "black box," we assume that the only accessible points of the system are the ac input terminals (Fig. 1). In this scenario, the dc-link between the motor and the ac input performs a filtering action, theoretically eliminating most of the information about the output circuits of the drive and the motor. In practice this does not thoroughly happen and any operating condition of the ac motor will appear on the ac side as a transient phenomenon or a sudden variation in the load power [3]. In particular, the presence of transient phenomena suggests an approach based on time-frequency analysis.

In [1], starting from the traditional Fourier approach, the authors proved that the presence of the harmonic components introduced by the nonideal switching of the rectifier can be readily detected. Applying the Park transformation, the effects of the bridge power switches are evident in the polar diagrams of the voltage and current Park vectors.

Unfortunately, this approach does not allow the extraction of synthetic parameters, significant enough to perform a reliable diagnosis.

The previous considerations led the authors to employ a multiresolution approach based on wavelets. In [4] it was shown that wavelets can help in the process of separating the information.

Wavelets are particular functions whose energy is concentrated both in time and frequency [5], [6]. They come in structured families, made of scaling function and wavelets created by rescaling and translating the mother wavelet. The mother gives the family its distinctive character in particular shape and resolution capability at a reference scale level. The wavelets allow the representation of details of a signal at different scales. Among

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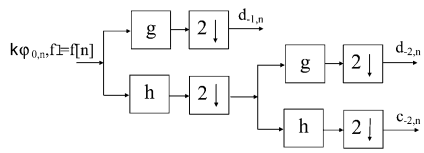

Fig. 2. Structure of the algorithm for the computation of the coefficients of the wavelet expansion.

the potentialities of this representation, the multiresolution allows the choice of the optimal time-frequency resolution. The time resolution can be different at different frequencies (always within the limits of the Heisenberg principle). For example, a family can be chosen so that the time resolution is particularly fine at high frequencies, allowing for the precise time identification of glitches or sudden very high frequency contents. On the other hand, the frequency resolution can be particularly good at lower frequencies, allowing for the monitoring of the frequency stability of the fundamental component. A wide variety of combinations of time-frequency resolution is possible and custom solutions are made possible by wavelet packets.

The approach proposed here involves the analysis of the signal through wavelet series decomposition. The decomposition results in a set of coefficients, each carrying local time-frequency information. An orthogonal basis function is chosen, thus avoiding redundancy of information and allowing for easy computation.

The computation of the wavelet series coefficients can be efficiently performed with the Mallat algorithm. The coefficients are computed by processing the samples of the signal with a filter bank as reported in Fig. 2. The coefficients of the filters are peculiar to the family of wavelets chosen as expansion basis. This algorithm is fully discrete.

The starting point is the projection of the signal on a reference space, that is, the calculation of the wavelet coefficients of the reference level of resolution, using $\varphi_{0,n}$ as the basis function for the reference space. The values of the coefficients are in fact the scalar product between $\varphi_{0,n}$ and the signal in the time-domain. If $\varphi_{0,n}$ has narrow limited support, we can infer that the values expected as inputs are the samples of the signal itself. This allows the first step of the algorithm. The filters $g[n]$ and $h[n]$ are high- and low-pass filters, respectively. Their coefficients depened on the chosen wavelet basis.

To reconnect the filter bank algorithm with the basic description of a wavelet system provided earlier, we can say that the algorithm is zooming out from the higher resolution level to the coarser resolution level.

Due to the time and frequency localization, the wavelet coefficients allow a compact representation of the signal. The features of the normal operating or faulty conditions are condensed in the wavelet coefficients. Conversely, the features of given operating modes can be recognized in the wavelet coefficients of the signal and the operating mode can be identified [7] and [8].

Employing the wavelet analysis, two preliminary results have been obtained:

1) identification of the drive operating conditions (faulty or normal operation);
2) identification of significant parameters for the specific condition.

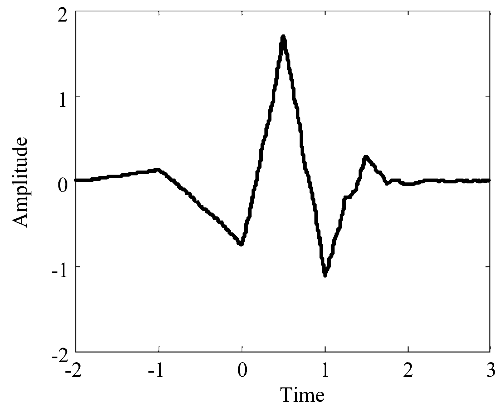

Fig. 3. Daubechies3 mother wavelet.

III. The Measurement System

An experimental setup has been implemented to verify the proposed theory. A DSP-based system acquires the field signals and performs the diagnostic algorithms.

The line voltage and current are acquired by an analog-to-digital conversion board (ADC), eight input channels with simultaneous sampling up to 500 kHz sampling rate on a single channel, ± 10 V range, 12-bit resolution and offset, and gain and nonlinearity error in the range $\pm 1/2$ LSB.

Voltage and current transducers have been specially realized in order to ensure an adequate insulation level between channels and between the supply and measuring devices over a wide band.

According to the input signal range (230 V rms for the voltages and up to 20 A rms for the currents) a noninductive, resistive voltage divider followed by an isolation amplifier was used as voltage transducer, and a closed-loop Hall effect transducer was used as current transducer [9].

The voltage transducers show a relative standard uncertainty on the gain of 0.02% and the current transducers show a relative standard uncertainty on the gain of 0.03% up to 5 kHz. The time delay at 50 Hz between the voltage and current channels is 20 μs and is constant up to 5 kHz [10].

Voltage and current are sampled at a 12.8 kHz sampling rate, so that 256 samples/period are acquired for a fundamental frequency of 50 Hz.

IV. The Measurement Algoritm

All measurement algorithms have been developed on the PC hosting the ADC board within a LabView virtual instrument environment. The wavelet algorithms have been implemented in a Matlab environment to allow quick coding.

As summarized in Section II, the wavelet analysis allows the separation of the information that identifies the main energy content and the superimposed noise [11]–[13]. The possibility of applying different bases for different applications adds a desirable degree of freedom. Recently, the idea of using a wavelet basis where the characteristics of the mother wavelet are close to those of the waveform under analysis has been applied with success in power electronic applications [12], [13]. The Daubechies wavelet basis is widely used in pattern recognition application for power quality disturbance detection [7]–[14]. Following this approach, six- and eight-coefficient Daubechies

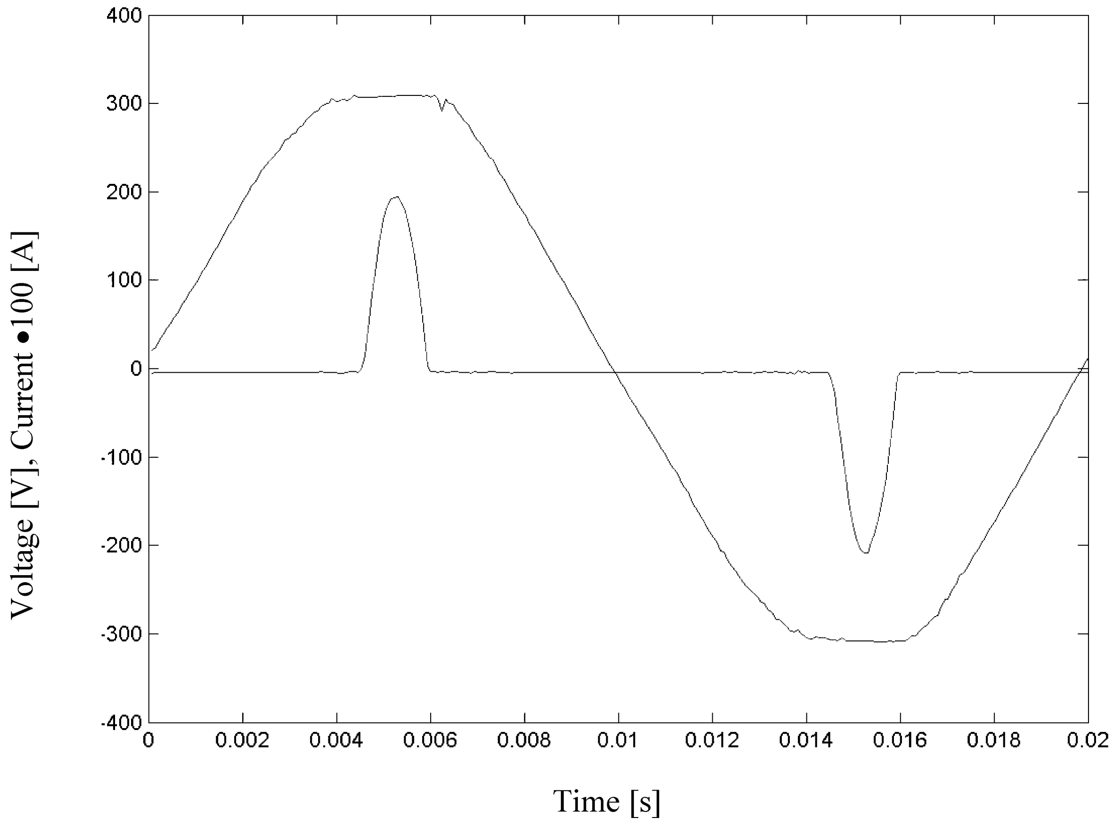

Fig. 4. Voltage and current in the measurement section.

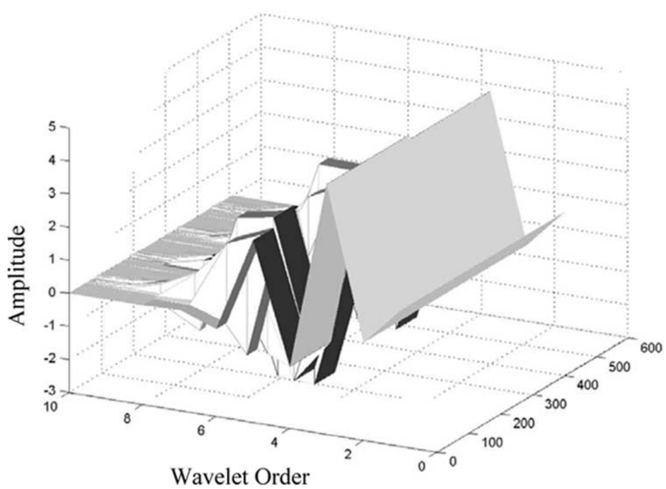

Fig. 5. Wavelet transform for a drive working under no-load conditions.

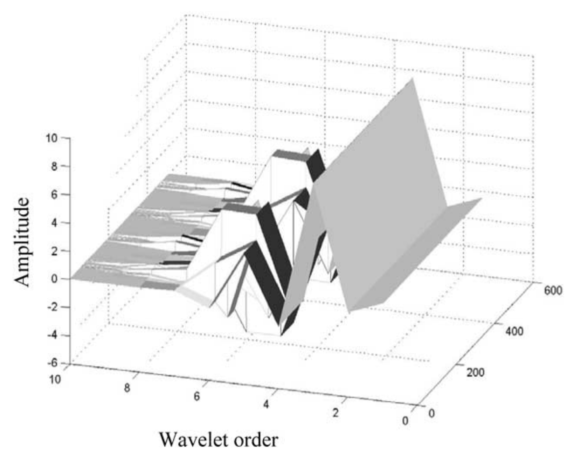

Fig. 6. Wavelet transform for a drive working at nominal load.

wavelets are considered. Daubechies wavelets are, among orthogonal bases, the better tradeoff between time and frequency localization. Depending on the application, in particular for what concerns power quality disturbances [7], it may be more convenient to use a longer or shorter filter. Daub3 is also the first one (in a list ordered by mother wavelet increasing support or vanishing moments) to be continuously differentiable [6] (with a good enough coefficient approximation). The related filter has six coefficients. This is the wavelet used in this application as a reasonable tradeoff between time and frequency localization, regularity, and number of filter coefficients.

In Fig. 3 the Daub3 mother wavelet is reported, while in Fig. 4 the waveforms of voltage and current at the measurement section are reported.

Data acquired in different operating conditions have been employed to test the effectiveness of the wavelet decomposition. In particular, the following conditions have been considered.

- The drive is working under no-load condition.
- The drive is working at nominal load.
- The drive is working with an open phase on the stator.
- The drive is working with an open phase on the rotor.

Different tests at different operating frequencies have been performed. The measurements performed in a variety of conditions on the actual drive were integrated with the results obtained from Virtual Test Bed (VTB) in simulation, using a validated model of the system.

Figs. 5 and 6 report the wavelet analysis for the drive working under no-load condition and at nominal load.

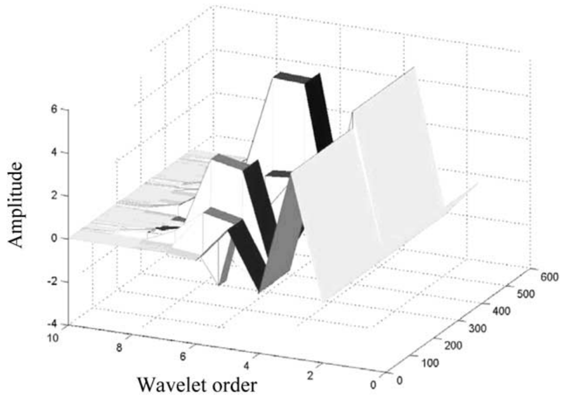

Fig. 7. Wavelet transform for open stator phase.

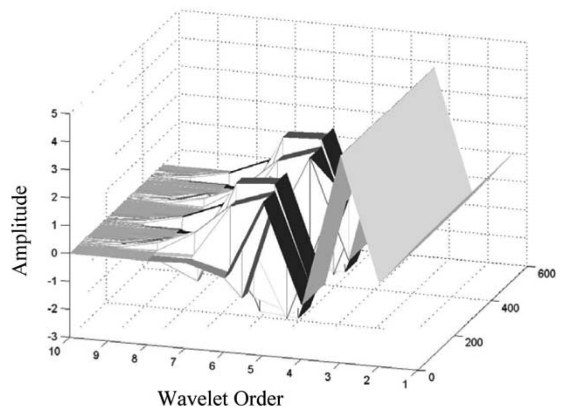

Fig. 8. Wavelet transform for open rotor phase.

The main differences between these two results are related to the amplitude of scaling function, mother wavelet, and first generation of wavelets. The reason for this can be found in the fact that the main difference between these two operating conditions is the amount of power delivered to the load. There are no specific asymmetry conditions to highlight.

The results are more interesting when a variety of fault conditions are considered.

In Fig. 7 one stator phase is open. This operating condition introduces a significant asymmetry in the first generation of wavelets. This suggests a possible index for the determination of this specific fault condition: comparison of the value of the coefficients of the first generation of wavelets.

In the same way we can analyze the results for the other type of fault conditions under consideration, shown in Fig. 8: one open rotor phase.

In this case, the weak coupling between the stator and the rotor of the induction machine reduces the effect on the first generation of the daughters. However, a check of the coefficients of the third generation revealed that the distribution in time is dramatically changed.

V. Fuzzy Logic Approach

The analysis presented in the previous paragraph allows the definition of a set of classification rules that can be applied as starting point for fuzzy sets definition.

Following this procedure, a complete automatic diagnostic system using a fuzzy-logic-based approach can be defined [15], [16].

Once the critical components for the diagnostic purpose are identified, a fuzzy clustering is adopted.

The idea is that we cannot identify one specific value defining "bad" or "good" condition: the status-index smoothly moves from a value that means "good" to us, to another that means "bad." The synthesis of this fuzzy system can be performed with the help of neural algorithms. In particular we decided to adopt a commercial software tool: the Adaptive Fuzzy Modeller by SGS-Thomson. This package is able to automatically define the fuzzy system parameters by applying neural algorithms. It is then possible to estimate the target function just by providing an input set of sampled data. Local rules can be introduced for local adjustments in the input–output function.

The training data obtained from actual measurements were integrated with data obtained from a simulation platform: the Virtual Test Bed [17]. The setup adopted for the simulation phase is a replica of the laboratory setup of the physical system. The scheme from the schematic editor is reported in Fig. 9.

The main blocks are the model of the three-phase inverter (grayish icon), the model of the induction motor, and the model of the mechanical load. The inverter has a built-in pulse width modulation (PWM) control and switching frequency of 4 kHz, the motor model has rotor windings made accessible for the purpose of fault condition simulation, and the mechanical part represents a viscous load. The other elements are represented according to the usual notation. The voltage source is operating at 220 V rms, 50 Hz.

The simulation is performed under normal load and no-load operating conditions for reference purpose. Then the rotor windings are opened one by one and the simulation in fault condition is performed in load and no-load conditions at different frequencies.

The output of the simulation (Fig. 10) is saved in a file. The current signals are then loaded by a Matlab program to perform wavelet processing (Fig. 11). The transformed data are manipulated and prepared for the subsequent training of the neurofuzzy tool. For each faulty or nonfaulty case an array can be built with the current coefficients in the wavelet domain corresponding to each time-sample. The maximum value of the wavelet transform over the whole time range is selected for each wavelet level. After this operation the array is turned into a vector with length equal to the number of family members and is next normalized in norm infinity.

In formulas, calling the generic wavelet coefficient w_{ij}, the input vector for the calculation of the diagnostic index is computed as follows:

$$D_j = \max_{i=1}^{n} \{|w_{ij}|\} \tag{1}$$

$$d_j = \frac{D_j}{\|D\|_\infty} \tag{2}$$

where i is the time index and j the index related to the wavelet family.

Each vector is known to be have been originated in fault or nonfault conditions, so it can be associated with a fault index equal to one or zero for the two different cases.

As a consequence, for any test case, we have a pattern composed by $n+1$ coefficients, with n being the wavelet order

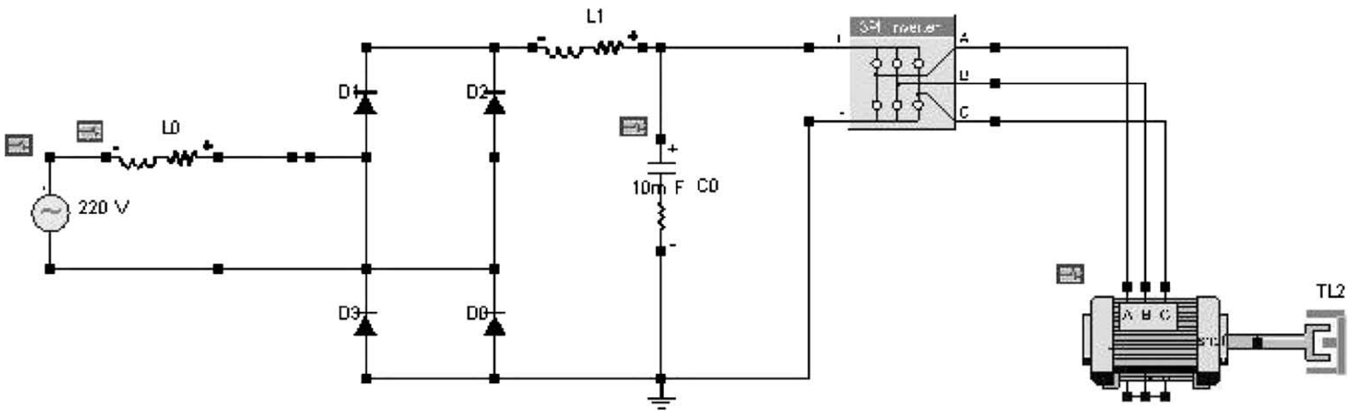

Fig. 9. VTB schematic of the system under test.

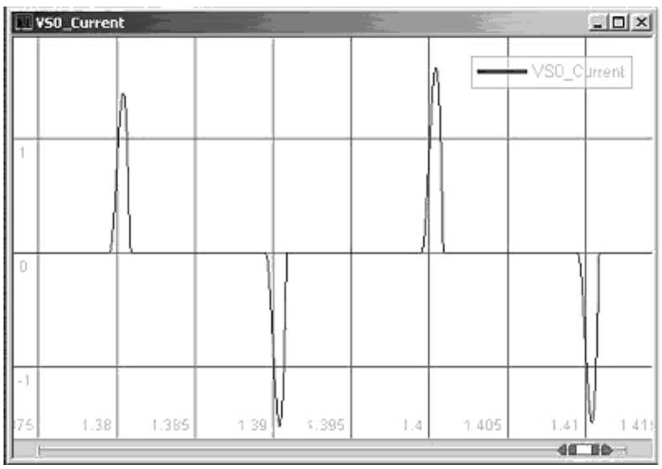

Fig. 10. Source current under no-load conditions (x-axis in [s] and y-axis in [A]).

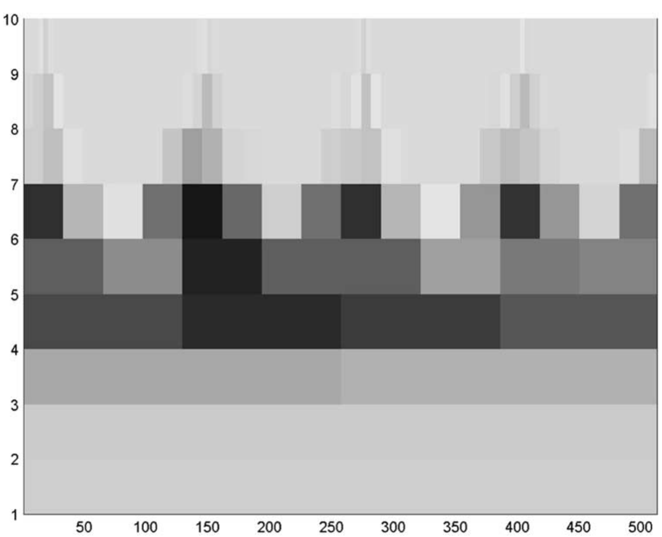

Fig. 11. Wavelet spectrum over the range of samples of two periods of the fundamental line frequency (samples versus wavelet order).

chosen for the transformation. A Matlab program performs automatically this processing, creating a data file ready for the neurofuzzy processing.

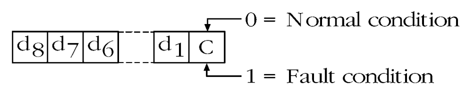

Fig. 12. The obtained pattern composed by $n+1$ coefficients.

Fig. 12 depict the obtained pattern composed by $n+1$ coefficients.

The neurofuzzy processing has been performed with the Adaptive Fuzzy Modeller by SGS Thompson. This package is able to automatically define the fuzzy system parameters by applying neural algorithms. It is then possible to estimate the target function just by providing an input set of sampled data. Local rules can then be introduced for a local adjustment in the input–output function.

In particular the synthesis of this fuzzy system is performed by two steps.

2) *Build Rule:* The automatic fuzzy rules identification is carried out thanks to an unsupervised learning on a winner-take-all fuzzy associatives memory neural network. Moreover, this step initializes the membership functions (Mbfs) position that will be optimized during the following step. Otherwise, it is possible to reduce the learning cycle rate by initializing manually the fuzzy sets and rule parameters. At the end of this first step a rule file containing the linguistic expression of the rules is generated.
3) *Build Membership Functions:* This step consists in the determination of membership functions and, in particular, this step allows the selection of the Mbf shape and the fuzzy intersection method for the project elaboration. Starting from the rule file supplied by the previous step, this second step initially associates to each fuzzy set a standard Mbf shape, which will be tuned during the learning phase in order to let the fuzzy system better approximate the process/function samples by means of subsequently running sessions. The Mbfs setting is carried out by a supervised learning on a multilayer backward-propagation fuzzy associative memory neural network that identifies the position and the shape of each Mbf. At the end of this second phase it is possible to graphically see the complete fuzzy set associated to each project variable. The synthesis proceeds automatically

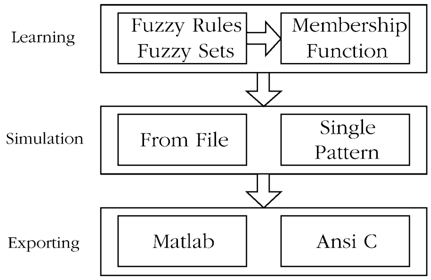

Fig. 13. Wavelet transform for a drive working under no-load conditions.

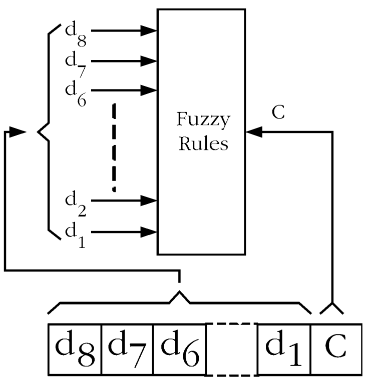

Fig. 14. The learning phase.

and the user can specify a set of very simple parameters such as the following.

a) *Number of membership function:* we used 3 for any input.

b) *Membership waveshape:* Before starting the Mbf parameters learning, it is necessary to define which kind of Mbfs—isosceles triangles, scalene triangles, or Gaussian shape—would be used. Gaussian membership kind was adopted in our application. This choice give the best performance in our application as found during the experimental activity.

c) *Fuzzy intersection operator:* It is necessary to define the fuzzy intersection operator applied during the inferencing phase. The fuzzy intersection operator represents the way to combine the membership degree of the antecedents of each rule. The used fuzzy intersection operator is the "minimum" operator even if even "product" operator is selectable.

Many cases have been adopted to perform the preliminary tuning of the neurofuzzy systems. Twelve selected cases are reported in Table I. A flow chart of these steps is depicted in Fig. 13. Moreover, Fig. 14 reports the learning phase.

A comparison of the results obtained from the fuzzy system with the real data is reported in Fig. 15 and in Fig. 16. Fig. 15 shows the status after 200 iterations of the learning algorithms while Fig. 16 reports the status after 400.

It is interesting to notice that the maximum local error is lower than 0.2 so that any results over 0.8 can be interpreted as fault and any result under 0.2 as safe conditions.

To thoroughly verify the capability of the system, a check was performed with a set of data obtained in a variety of operating conditions and not used for the training phase. Such a test shows whether the system is able to interpolate the results for conditions that have not been previously considered.

TABLE I
THE SELECTED TUNING CASES

Frequency [Hz]	Load	Fault
20	No load	No fault
30	No load	No fault
50	No load	No fault
20	No load	Rotor ph. Open
30	No load	Rotor ph. Open
50	No load	Rotor ph. Open
20	No load	Stator ph. Open
30	No load	Stator ph. Open
50	No load	Stator ph. Open
20	Nominal load	No fault
30	Nominal load	No fault
50	Nominal load	No fault

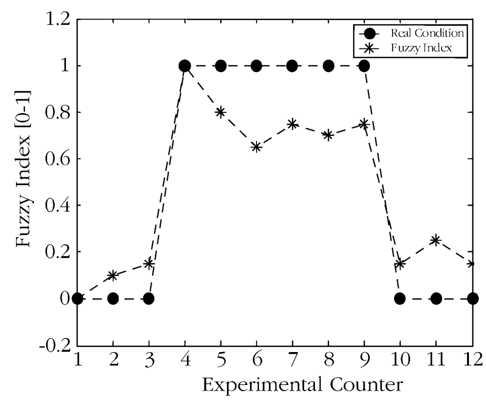

Fig. 15. Fuzzy simulation after 200 epochs (x-axis number of testing case, y-axis fuzzy index).

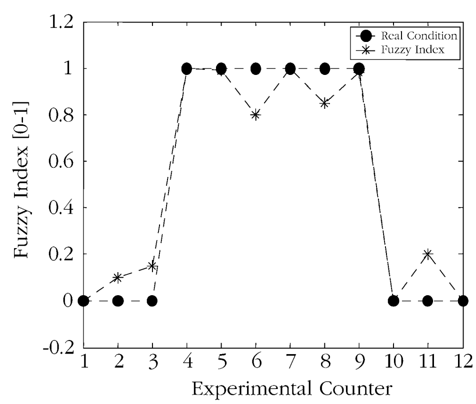

Fig. 16. Fuzzy simulation after 400 epochs (x axis number of testing case, y-axis fuzzy index).

In particular, the data reported in Table II have been used for testing purposes. The outcome of the verification is really promising. As can be deduced from Fig. 17, the neurofuzzy system was able to detect the operating condition with a high

TABLE II
THE TEST CONDITIONS

Frequency [Hz]	Load	Fault
10	No load	No fault
20	No load	No fault
50	Nominal load	Stator ph. Open

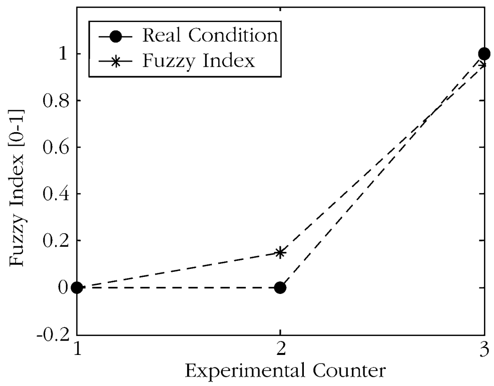

Fig. 17. Extra test cases not applied during the learning phase. (x-axis number of testing case, y-axis fuzzy index).

level of confidence even if the pattern was not included in the training set.

VI. CONCLUSION

The results shown in this paper confirm the possibility to design a diagnostic system for an ac drive using only current measurements collected at the ac power input side.

Currently, the system is able to provide an index, obtained by fuzzy processing, that can be used to identify alert conditions. The fuzzy index has been tested with data used for the training phase and data never used during the training phase. In both cases the algorithm was able to identify the operating condition with high level of likelihood.

In a further extension of the work, the authors will investigate the capability of the algorithm to identify the specific faulty condition that activates the fuzzy index. For this purpose, a set of neurofuzzy systems working in parallel will be instructed.

The software tools adopted for the research are all public domain (Virtual Test Bed for simulation, WaveLab for wavelet analysis, and Adaptive Fuzzy Modeler for neurofuzzy processing). The innovative routines written by the authors are in Matlab standard code. The authors are available for more details and sharing of experiences.

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