IMTC 2003 – Instrumentation and Measurement
Technology Conference
Vail, CO, USA, 20-22 May 2003

A Neuro-Fuzzy Application for AC Motor Drives Monitoring System

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Abstract ***– Nowadays industrial applications require suitable monitoring systems able to identify any decrement in the efficiency involving economical losses. This paper shows that the information coming from a general purpose monitoring system can be usefully exploited to realize a sensorless instrument able to monitor an ac motor drive and a diagnostic tools providing useful risk coefficients. The method is based on a complex digital processing of the line signals acquired by means of a Virtual Instrument. The employed wavelet algorithms have been implemented in a Matlab environment and risk coefficients are elaborated by means of a suitable neuro fuzzy algorithms.***

Keywords ***– Virtual Instruments, Neuro – Fuzzy, Virtual Test Bed.***

I. INTRODUCTION

A monitoring system can be defined as a set of devices, procedures and diagnostic tools to follow every single step of a process.
Every industrial application requires a suitable monitoring system of the related process in order to identify any decrement in the efficiency involving economical losses. Early detection of operating conditions of the apparatus that deviate from the optimal may avoid subsequent failures, or even faults.

In a previous paper [1] the authors showed that the generic information coming from a measurement system for electric power monitoring the power consumption of an electric load can be usefully exploited to realize a sensorless instrument to monitor an AC motor drive, so that useful information about the drive status can be obtained. The capability of the DSP-based instruments to execute complex algorithms in real time makes the implementation of continuous monitoring functions possible, giving the opportunity to realize dedicate remote monitoring activity for a set of electric loads in a large plant [12].

The opportunity to combine diagnostic and monitoring operations on an AC motor drive without using dedicated sensors cannot achieve a diagnosis as reliable as that provided by totally customized systems [2]. 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 transform such as wavelets and fuzzy computation is used [3,13]. Fuzzy indexes can be considered risk coefficients giving the user the likelihood to be 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 to 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 so that this section should theoretically eliminate most of the information about the output circuits of the drive and the motor. In practice this is not completely true and any operating condition of the AC motor should appear on the main side as a transient phenomenon or sudden variations in the load power [2]. In particular, the first consideration suggests an approach based on time-frequency analysis.

In [1], starting from the traditional Fourier approach, the authors have proved that the presence of the harmonic components introduced by the non-ideal 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 doesn't allow the extraction of synthetic parameters significant enough to perform a reliable diagnosis.

The previous considerations suggested the authors to employ a multi-resolution modelling based on wavelets. In [13] was proved 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, 10]. They come in structured families made of mother, father and daughters, created by rescaling and translating the parents. The mother and the father give the family its distinctive characters that are the shape of the functions and their resolution capability at a reference level. The daughters allow the representation of details at different scales. Among the potentialities of this representation, the multi-resolution allows the choice of the most convenient time-frequency resolution. The time resolution can be different at different frequencies (always in 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 the precise time identification of glitches or sudden very high frequency contents. On the other hand, the frequency resolution could be particularly good at lower frequencies, allowing the monitoring of the stability of the fundamental component. A wide variety of combinations of time-frequency resolution is possible and custom solution are made available 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 easy computation.

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

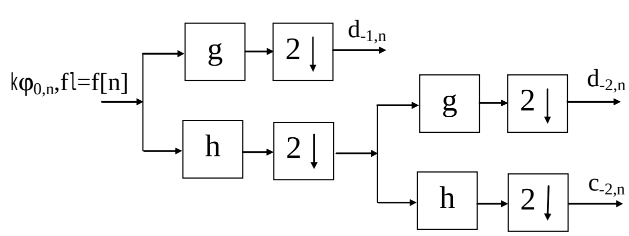

Fig. 1 - Structure of the algorithm for the computation of the coefficients of the wavelet expansion.

The starting point is the projection of the signal on a reference space, in other words, the wavelet coefficients of the reference level of resolution, since $\varphi_{0,n}$ is a 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 starting of the algorithm. The filters g and h are high-pass and low-pass filters respectively.

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 operating or faulty conditions are condensed in the wavelet coefficients. Conversely the features of a given operating modes can be recognized in the wavelet coefficients of the signal and the operating mode can be identified.

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.

III. THE MEASUREMENT SYSTEM

An experimental set-up 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), 8 input channels with simultaneous sampling up to 500 kHz sampling rate on a single channel, ±10V range, 12-bit resolution and offset, gain and non-linearity error in the range ±½ 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 non-inductive, resistive voltage divider followed by an isolation amplifier was used as voltage transducer, and a closed-loop Hall effect transducers was used as current transducer [11].

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 [4].

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

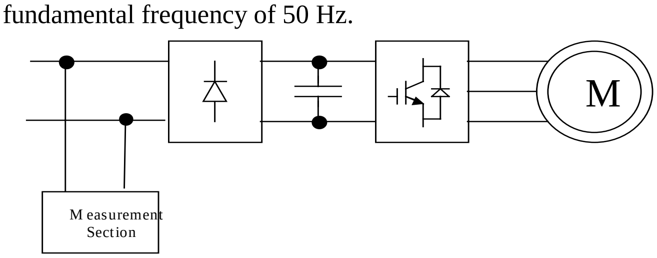

Fig. 2 - scheme of the system under test

IV. THE MEASUREMENT ALGORITM

All measurement algorithms have been developed on the PC hosting the ADC board under a 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 identifying main energy content and superimposed noise [3, 8, 9]. On the other hand, the possibility to apply different bases for different applications can be considered as an interesting 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 [8,9]. Following this approach, Daubehcies6, Daubechies8 and the order 3 Battle-Lemarie bases was considered. Daubechies wavelets are, among orthogonal basis, the better tradeoff between time and frequency localization. Daubechies6 is also the first one (in a list ordered by increasing support or vanishing moments) to be continuously differentiable. The related filter has 6 coefficients. This is the wavelet used in this application as a reasonable trade-off between time and frequency localization, regularity and number of filter coefficients.

In Fig. 3 the Daubechies6 mother wavelet is reported while in Fig. 4 the waveforms of voltage and current at the measurement section are reported.

Data acquired for different operating conditions have been employed to test the effectiveness of the wavelet function. 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 for different frequencies have been performed. The measurements performed in a variety of conditions on the actual drive were integrated with the results obtained from VTB in simulation, using a validated model of the system.

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

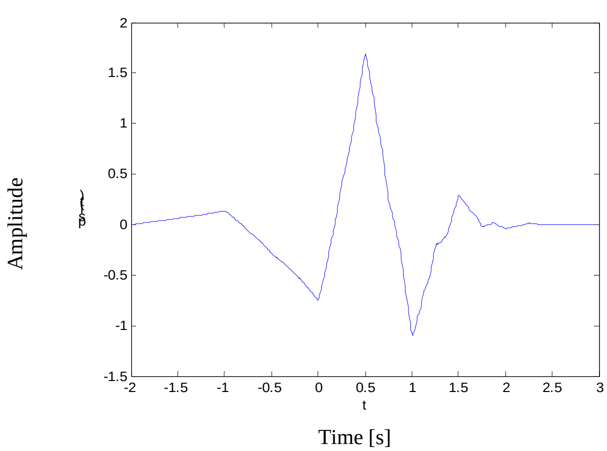

Fig. 3 - Daubechies6 mother wavelet.

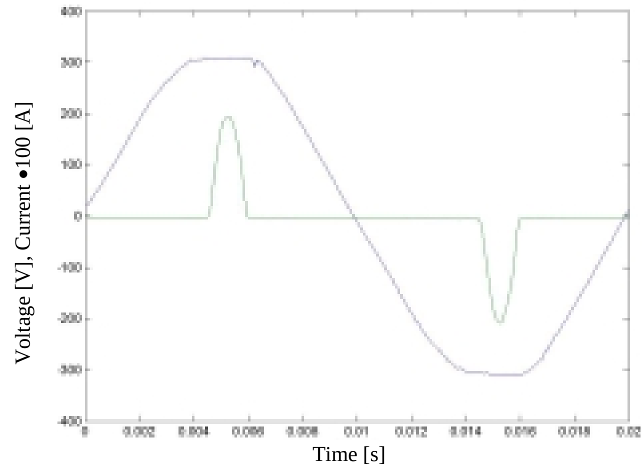

Fig. 4 - Voltage and current in the measurement section.

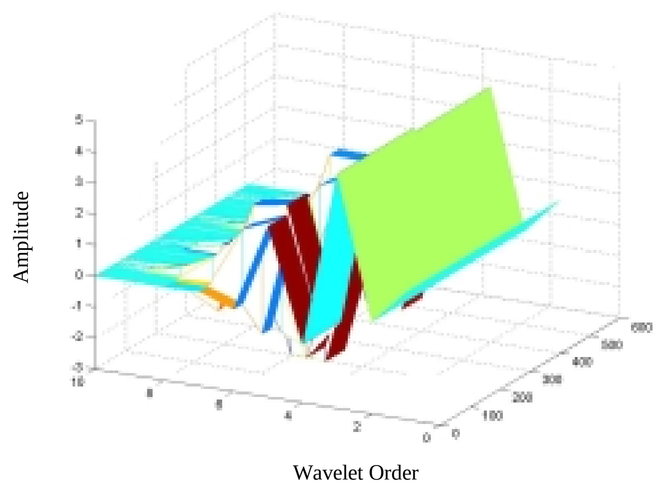

Fig. 5 - Wavelet transform for a drive working under no-load conditions.

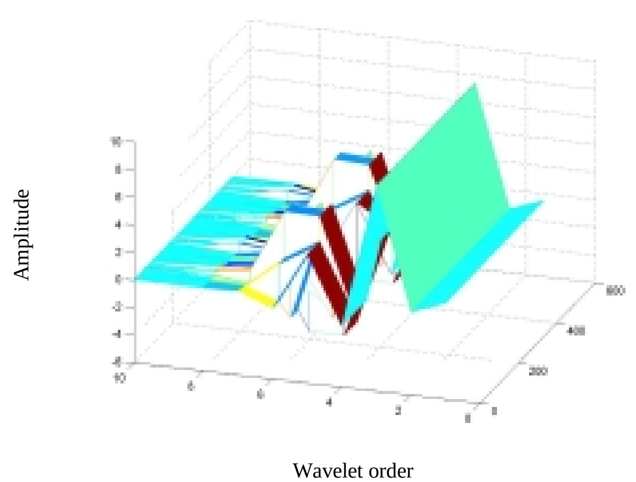

Fig. 6 - Wavelet transform for a drive working at nominal load.

The main differences between these two results are related to the amplitude of father, mother and first daughter. This makes sense because the main difference between these two operating conditions is the amount of power delivered to the load. There are no specific asymmetry conditions to evidence.

The situation becomes more interesting when some fault condition is considered.

In

Fig. 7 a stator phase is open. This operating condition introduces a main asymmetry for the first generation of daughters. This suggests a possible index for the determination of this specific fault condition: comparison of the value of the first generation daughter.

In the same way we can analyze the results for the other fault condition shown in

Fig. 8: one rotor phase open.

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

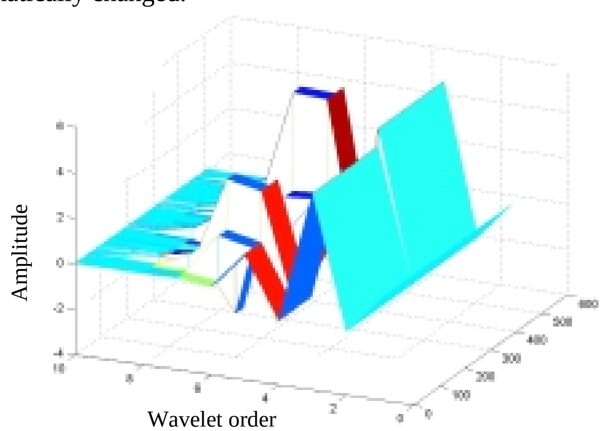

Fig. 7 - Wavelet transform for open stator phase.

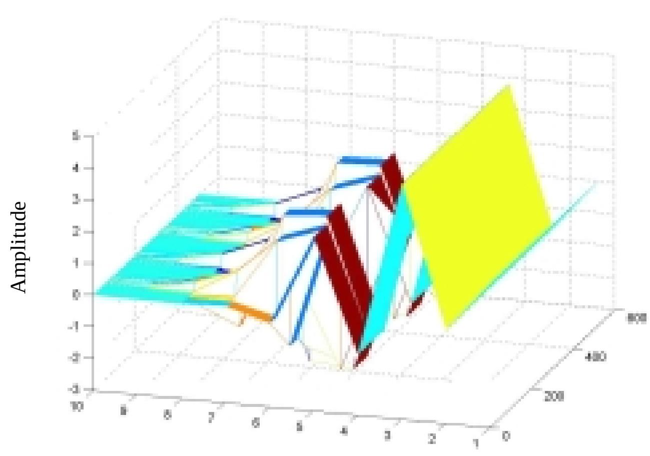

Fig. 8 - Wavelet transform for open rotor phase.

V. FUZZY LOGIC APPROACH

In effect, 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 fuzzy-logic based approach can be defined [6, 7].

Once we identify the critical components for the diagnostic purpose a fuzzy clustering is adopted.

The idea is that we can not identify a specific value defining a "bad" or a "good" condition: we can smoothly move from a situation that is defined as" good" to something we define as "bad". The synthesis of this fuzzy system can be performed with the help of neuro algorithms. In particular we decided to adopt a commercial software tool: the Adaptive Fuzzy Modeller (AFM) 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 a local adjustment in the input-output function.

The training data actual measurement were integrated with data obtained from a simulation platform: the Virtual Test Bed [14]. The platform adopted from the simulation phase is a perfect replication of the lab set-up that is going to be applied. The scheme from the Schematic Editor is reported in Fig. 9.

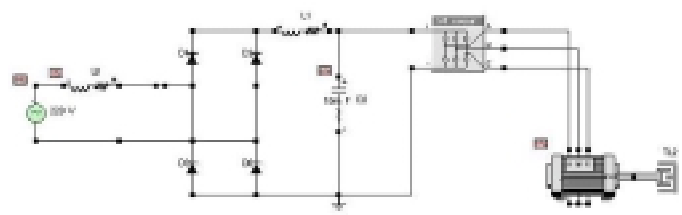

Fig. 9 - VTB schematic of the system under test.

To be noted in particular are the model of the three-phase inverter (greyish icon), the model of the induction motor and the model of the mechanical load. The inverter has a built-in PWM control and switching frequency of 4 kHz, the motor model has rotor windings made available 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 220V RMS, 50Hz.

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

The output of the simulation is saved in a file. The current current signals are then loaded by a Matlab program to perform wavelet processing.. The transformed data are manipulated for the subsequent training of the neuro-fuzzy tool. For each fault or non-

fault case an array can be built with the values of current 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 it's 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:

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

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

where i is the time index and j the index related to the wavelet family.
Each vector is known to be originated in fault or non-fault conditions, so it is associated with a fault index equal to 1 or 0 for the two different cases.

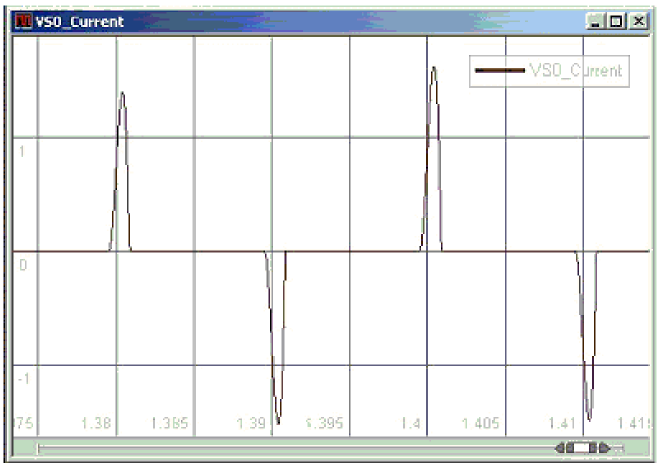

Fig. 10 - Source current under no-load conditions (x-axis in [s] and y-axis in [A]).

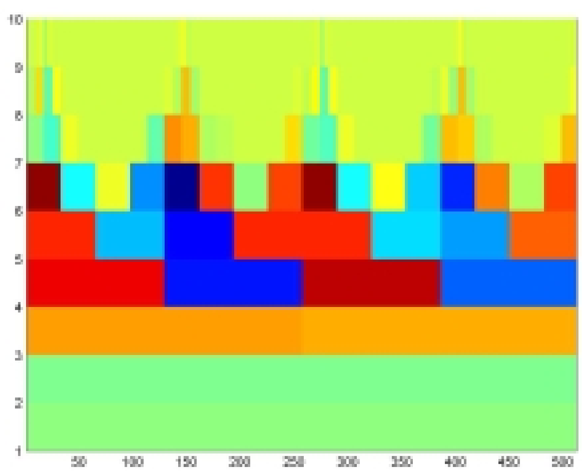

Fig. 11 - Wavelet spectrum over the range of samples of two periods of the fundamental line frequency (samples vs wavelet order).

As a consequence, for any test case we have a pattern composed by n+1 coefficients if n is the number of wavelet families adopted for the transformation. A Matlab program performs automatically this processing creating a data file ready for the neuro-fuzzy processing.
The neuro-fuzzy processing has been performed by using the Adaptive Fuzzy Modeler 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.
The synthesis process proceeds automatically and the user can specify a set of very simple parameters such as:

- Number of membership function: we used 3 for any input,
- Membership waveshape: we adopted gaussian membership.

Twelve cases have been adopted to perform the preliminary tuning of the neuro-fuzzy systems. The selected cases are reported in the following table.

Table 1 - Table of 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

A comparison of the results obtained from the fuzzy system with the real data is reported in Fig. 12 and in Fig. 13.

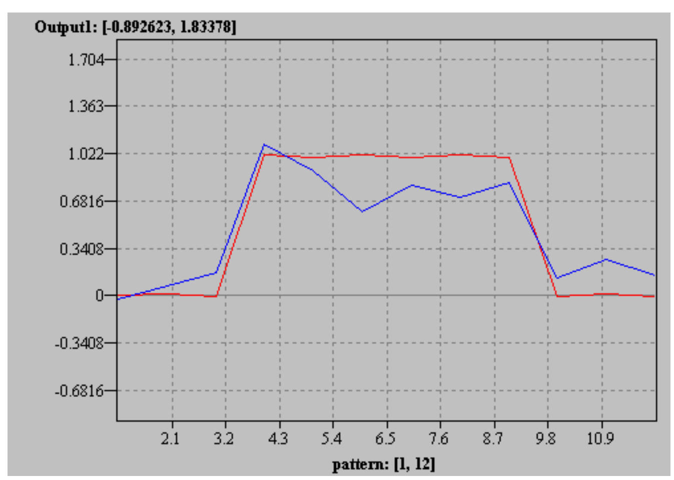

Fig. 12 - Fuzzy simulation after 200 epoch.

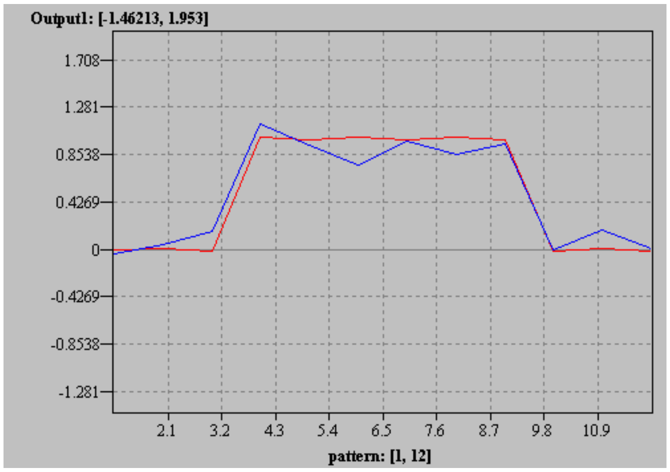

Fig. 13 - Fuzzy simulation after 400 epoch.

The first case is obtained after 200 iterations of the learning algorithms while the second 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 a safe conditions.

To better verify the capability of the system a set of tests have been also performed for conditions that were not included in the training pattern to check if the system is able to interpolate about conditions that have not been considered in advance.

In particular, the test conditions data reported in table 2 have been used for testing purpose.

Table 2 - Table of the test conditions.

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

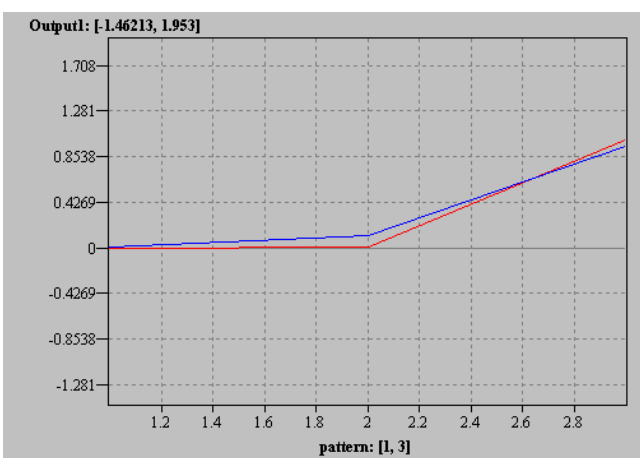

Fig. 14 - extra test cases not applied during the learning phase.

The results are really promising also for this case. As it can be deduced from Fig. 14 the neuro-fuzzy system was able to detect the operating condition with high level of confidence even if the pattern was not included in the training set.

VI. CONCLUSIONS

The results shown in this paper confirm the possibility to design a diagnostic system for an AC drives starting from current measurement on the input side.

The authors are currently working on a further experimental phase to test the fuzzy system with new experimental data coming from the used system. This means that we expect to be able to perform the testing activity without repeating the learning phase. A success on this step will demonstrate not only the possibility to implement the platform but also the possibility to perform the training of the system by using simulated data. This last point is extremely interesting for diagnostic purpose because it will not require to perform any test on damaged equipment.

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