Diagnostics of ball bearings in varying-speed motors by means of Artificial Neural Networks

Marco Cocconcelli and Riccardo Rubini
University of Modena and Reggio Emilia
Reggio Emilia, 42122, Italy
Tel. (+39) 0522 52 2671, Fax (+39) 0522 52 3609
{marco.cocconcelli, riccardo.rubini}@unimore.it

R. Zimroz and W. Bartelmus
Diagnostics and Vibro-Acoustics Science Laboratory
Pl Teatralny 2, Wroclaw, 50-051, Poland
Tel. (+48 71) 320 68 49, Fax (+48 71) 344 45 12
{radoslaw.zimroz, walter.bartelmus}@pwr.wroc.pl

Abstract

This paper deals with the diagnostics of ball bearings in direct-drive motors by means of Artificial Neural Networks (ANN). Direct-drive motors are becoming commonly used in automatic machines, e.g. in the field of packaging, since these motors are easily driven by the control system to perform polynomial profiles of motion avoiding the presence of gears train or cams between the motor and the load. An ordinary task of the motor involves continuous changes of the shaft speed and a cyclic inversion of its rotating direction. The continuous change of rotational speed of the motor represent the main drawback in terms of diagnostics of the ball bearing, since the large part of algorithms proposed in the literature need a constant rotation frequency of the motor to identify fault frequencies in the spectrum. In this paper the use of Artificial Neural Networks overcomes the constant-speed limits and they are proven to be a powerful tool to diagnose the health of ball bearing even in variable-speed applications.

1. Introduction

Ensuring continuity of production in the enterprise on a global scale is one of the key requirements. Modern production lines are automated, highly efficient, but unfortunately they are not devoid of common problems in maintaining the machines. To avoid unexpected failures apply monitoring and diagnostics(1-8). However, the classic, i.e. the existing solutions, successfully used for years in the petrochemical, paper, mining, etc. industry, cannot be always applied because of specific design solutions.
In literature the diagnostics of ball bearings is based on the idea that to each failure mode of a bearing is associated a characteristic frequency signature in the spectrum, that can be extracted by an appropriate analysis of a vibration signal. However, most of the existing studies are based on a very important assumption, in other words that the motor is running at constant speed, accounting at most the presence of limited fluctuations around a “target” value(9-13). The assumption of constant rotation speed, which still holds true for many applications, becomes nevertheless a huge limitation in the field of automatic machines, where usually a number of servomotors (or also called “direct-

drive" motors) are employed as electric cams in order to track variable velocity profiles. Servomotors (usually AC brushless motors) tend to appear more and more often in recent machine designs, as their performances are more flexible than the mechanical solutions for machine motion with respect to the time required to reconfigure the motion profile, since the absence of mechanical cams or gear reduction.
In such conditions, of course, any detection method based on frequency signature detection is bound to fail.
In this paper an original solution is proposed that is based on National Instrument hardware for data acquisition, simple feature extraction from available data, and finally decision making supported by Neural Network.
Jardine et al.[(1)] gives a simple and clear description of Artificial Neural Network (ANN): "An ANN is a computational model that mimics the human brain structure. It consists of simple processing elements connected in a complex layer structure which enables the model to approximate a complex non-linear function with multi-input and multi-output. A processing element comprises a node and a weight. The ANN learns the unknown function by adjusting its weights with observations of input and output. This process is usually called training of an ANN. There are various neural network models. Feedforward neural network structure is the most widely used neural network structure in machine fault diagnosis". Although several paper have been proposed in literature covering different pre-processing techniques together with ANN[(14-21)], their use on this specific speed-varying application (i.e. direct drive motors) has never been investigated before.
The main features of the system expected by the potential client are: quick (online), reliable, effective (in sense of diagnostics) and cheap. From diagnostic point of view a problem of damage detection in this case is also very demanding, mainly due to time varying operation of machine (will be discussed later). Using signal processing language, one may say that we have impulsive noise detection problem (as a signature of bearings damage) in presence of also cyclic (duration is different), impulsive signal with much higher energy (it comes from packaging process) All these requirements directed our investigation to presented materials.
The paper is organized as follow: in Section 1 the experimental setup is described with a brief description of the industrial application and the hardware used during the test. Section 2 focuses on the pre-processing of the data. Since the mathematical formulation of the ANN is made by a commercial software, the main contribution of paper consists in this crucial part of the ANN application. The proposed architecture of ANN and the experimental results are collected in Section 3, while conclusions close the Section 4 and the paper.

1. Experimental setup

This paper is based on data acquired for an industrial application. A MPL-B680B AC brushless motors by Rockwell Automation is directly connected to a complex crank mechanism by means of a belt which radial loads the shaft of the motor. The patented crank mechanism is the core part of an automated machine for packaging, it cannot be described due to confidential agreement but from a dynamics point of view it is a cyclic load acting on the shaft and it is no-stationary due to the interaction between the mechanism and the packaging material. The toothed belt is preloaded of 4kN, and the more stressed bearing of the motor is the closest to the pulley, a NSK 6309 single-raw ball bearing.

An amount of 13 bearings are available, 7 of them are healthy and 6 are faulted. In particular, the healthy bearings are classified in two sets: 3 are brand-new healthy bearings, 4 are bearings which ran for 1000 hours, then opened without any evidence of fault and classified as healthy. The faulty bearings are also divided in two sets: 2 bearings have been artificially damaged in the lab of the University and 5 come from the field, that is from other industries that claimed the motors as damaged. The artificial fault has been hand made by means of a DREMEL 300 tool equipped with a 2,4mm engraving cutter (DREMEL 108). A small engrave of about 1 mm of width and long as the depth of the bearing has been cut away on the outer or inner race, in order to be sure that the rolling elements hit the damage during the working condition. In all the cases coming from the field the bearings have been opened at last, and a generalized faults on both the inner and outer race were always present.

An amount of 11 bearings – between those available – have been tested in three conditions: an hourly capacity of 2500 packs per hour (pph), 3500 pph and 4500 pph. In these three cases the running profile of the motor is almost the same but the mean speed is increased to get to the established capacity of the machine. Figure 1 shows the motion profile of the shaft in the three different capacities, while Table 1 the hourly capacity tested, the subsequent period for the single pack, the number of complete cycles stored during a single run of acquisition and the number of bearings tested at each capacity. The unit of the ordinate axis has been intentionally leave it blank due to a confidential agreement between the authors and the industry.

The vibration signal has been acquired by means of an accelerometer MTN 1100 CQ mounted on the motor in the load direction of the belt. The signal was connected to a NATIONAL INSTRUMENTS acquisition board, made by a CDAQ-9172 back plane upon which a NI-9233 module collected the accelerometer output. The data from acquisition board was stored on a laptop via its USB interface and later post-processed with MATLAB. The sampling frequency used is 10kHz and the single acquisition lasted 50 seconds.

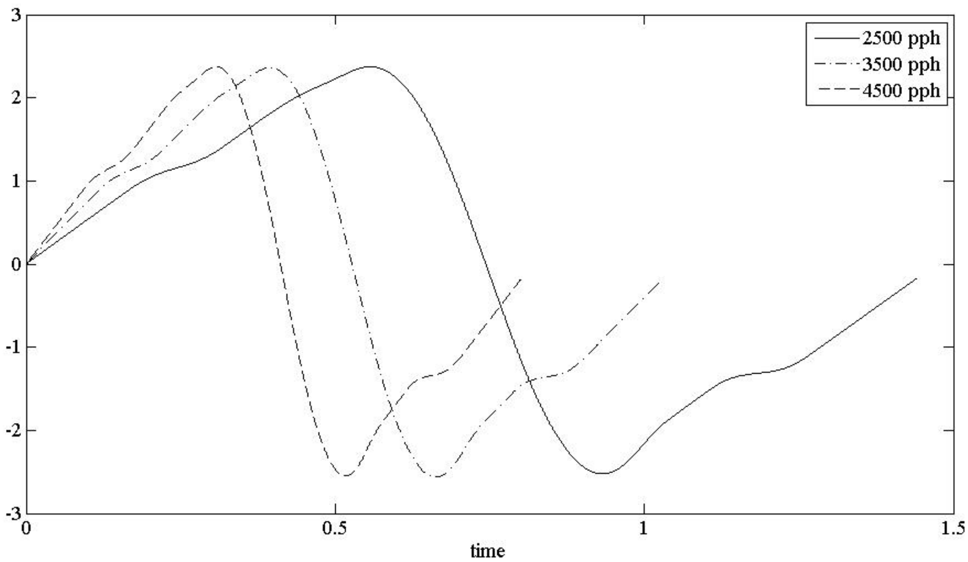

Figure 1. Motion profile of the shaft for different hourly capacity of the machine

Table 1. Hourly capacities tested for the packaging machine

Hourly capacity (pph)	Pack period (s)	Number of cycles in a single run	Number of bearings tested at given capacity
2500	1.44	34	11
3500	1.029	48	13
4500	0.8	62	11

2. Preset of data

In this section the focus is put on the definition of input and output arrays for the ANN, and on the discussion about the number of data available to test and training the net.
Since the mathematical core of the net is already set by the specific software used, as it will be explained in section 3, the aim of the research focuses on the definition of an appropriate set of quantities which would allow the net to easily recognize the health status of the bearing. On the other side the choice of the output parameter is unavoidable to all practical purposes, the small amount of disposable data are not enough to discriminate between different kind of faults (e.g. outer rather than inner fault). A proposal to increase the number of the data set used in the training and test of the net closes the section.

2.1 Definition of the input array

One of the most used parameter to assess the health condition of a machinery is the root-mean-square (RMS) value of the vibration data. The RMS is defined as reported in Equation (1), where the sum is extended to all the *N* sample acquired.

$$RMS = \sqrt[2]{\frac{\sum_i^N x_i^2}{N}} \qquad (1)$$

Figure 2 shows the RMS value for each of the bearing as a function of the hourly capacity of the machine. In order to explain better the results, the results for each capacity is split in two columns, the left one for faulted bearings and the right one for healthy bearing. In particular the plot reports the mean value of the RMS computed over a single cycle to be independent on the specific time-history acquired.
Figures 2 gives two feedback: the RMS value for the faulted bearings is quite higher than for the healthy one under the same conditions of capacity. There is only one exception for 3500 pph, where a single bearing shows an unlikely value even bigger than the most noisy faulted bearing. Unfortunately the data set available for that specific bearing is a single acquisition at 3500 pph, then it is not possible to compare it with the rest of data in different conditions. Since part of the data have been acquired directly by the staff of the industry, the unexpected value of RMS could be due to unknown causes which haven’t been reported in the acquisition log.
It will be now acceptable two working hypothesis: considering acceptable all the data available, included the noisy healthy bearing, rather than removing that single test assumed to be incorrect and keeping the remaining data. In the following of the paper both hypothesis will be carried on.

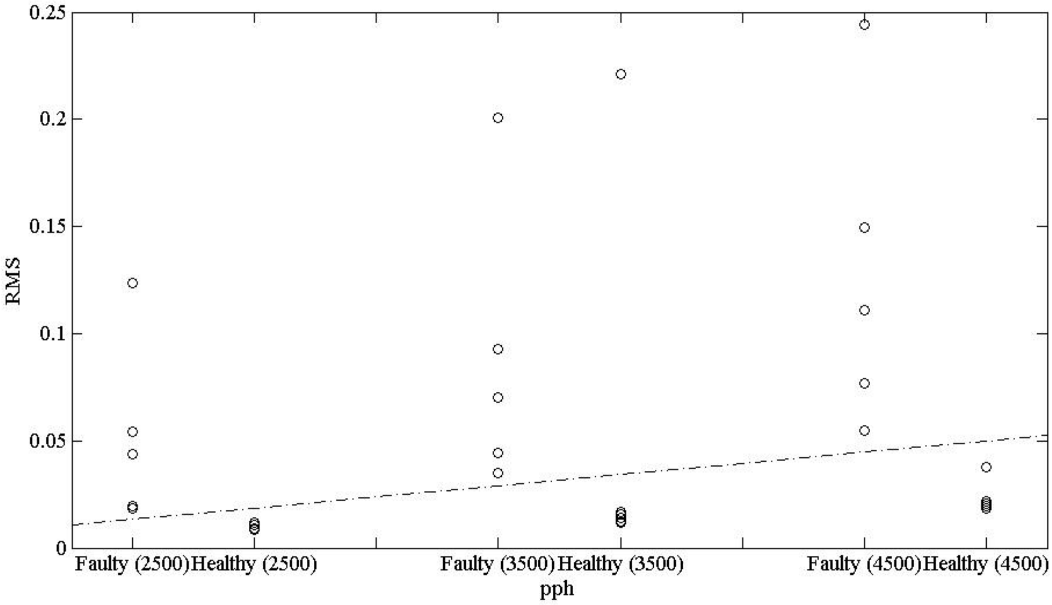

Figure 2. RMS value of vibration data versus the hourly capacity of the machine

The second feedback coming from Figure 2 is the importance of the hourly capacity of the machine. In fact the RMS value for a healthy bearing working at 4500 pph is comparable to the RMS for some of the faulted bearings working at lower capacity.

Under the assumption of rejecting the data that produced the uncommon value of RMS for a healthy bearing in Figure 2, the diagnostics of ball bearings for this specific industrial application seems to be straightforward.
In particular Figure 2 suggests the possibility to trace a line that divides the healthy bearings from the faulted, as a function of the hourly capacity of the machine. Considering the lowest values of RMS for faulted cases and the higher values for the healthy ones, the linear least squares method allows to find the line equation reported in Equation 2 and showed in Figure 2 in dash-dotted line:

$$f(x) = 0.01563 \cdot \left(\frac{x - 3500}{1000}\right) + 0.02914 \tag{2}$$

where x is the hourly capacity in pph and f is the RMS value of the vibration measured over a single cycle of the machine. This RMS value is assumed to be the threshold between an acceptable condition of the bearing and an alarm condition for the substitution of the component. In that specific case there no need to introduce an ANN since Equation (2) is sufficient to discriminate between the two possible states of the bearing.

In case that all data are assumed acceptable, the net needs another input to settle the unexpected value of RMS of the noisy bearing. A well-known parameter used in diagnostics of bearing is the kurtosis, defined as the fourth standardized moment, that is the ratio between the fourth moment about the mean and the standard deviation raised at the fourth power, as shown in Equation 3:

$$k = \frac{E(x-\mu)^4}{\sigma^4} \tag{3}$$

where μ is the mean of x, σ is the standard deviation of x, and $E(t)$ represents the expected value of the quantity t. In the literature several authors suggest the use of the kurtosis to identify the presence of impulsive effects such impacts due to the presence of a damage. A white noise random signal follows the Gaussian normal probability function and then the kurtosis is equal to 3, while the presence of spikes in the signal increase the variance of the distribution and accordingly the kurtosis value increases.
Figure 3 shows a plot analogous to that of Figure 2 but the ordinate axis reports the kurtosis value. In particular the value of kurtosis for all the healthy bearings is much more coherent, that is they are comparable to each other, even if in different cases the kurtosis is not sufficient to diagnose the health of the bearing – especially if the value is close to 20.
The trend of kurtosis for an healthy bearing seems to be linearly dependent of the capacity of the machine, while this contribution is not relevant when the bearing is faulted.

Figure 4 shows the proposed input array to the ANN is made of three element for each acquisition:

- RMS value
- Kurtosis value
- The hourly capacity of the machine

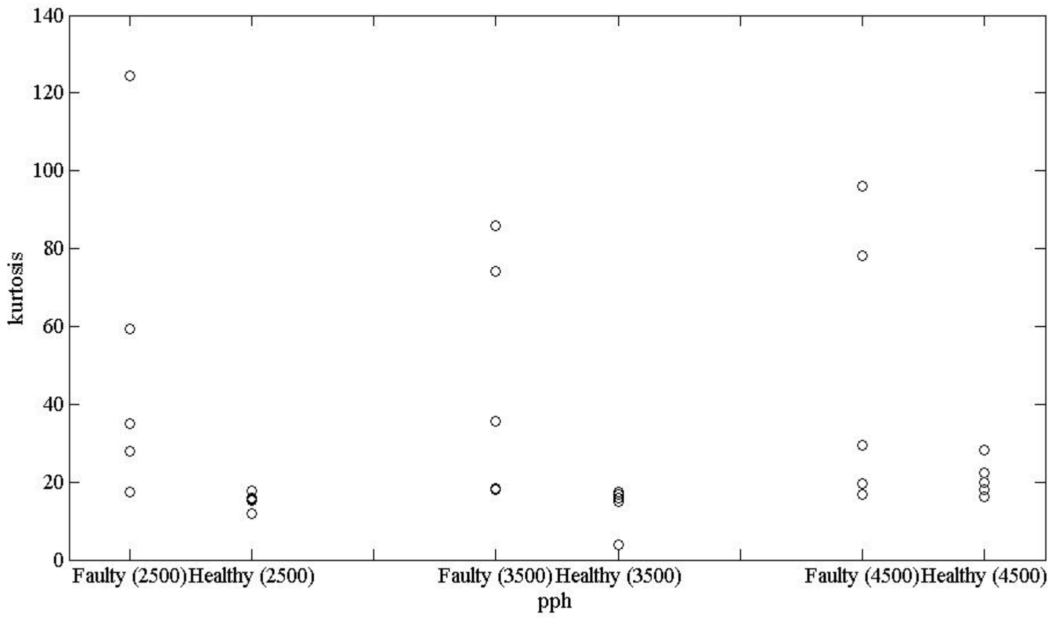

Figure 3. Kurtosis value of vibration data versus the hourly capacity of the machine

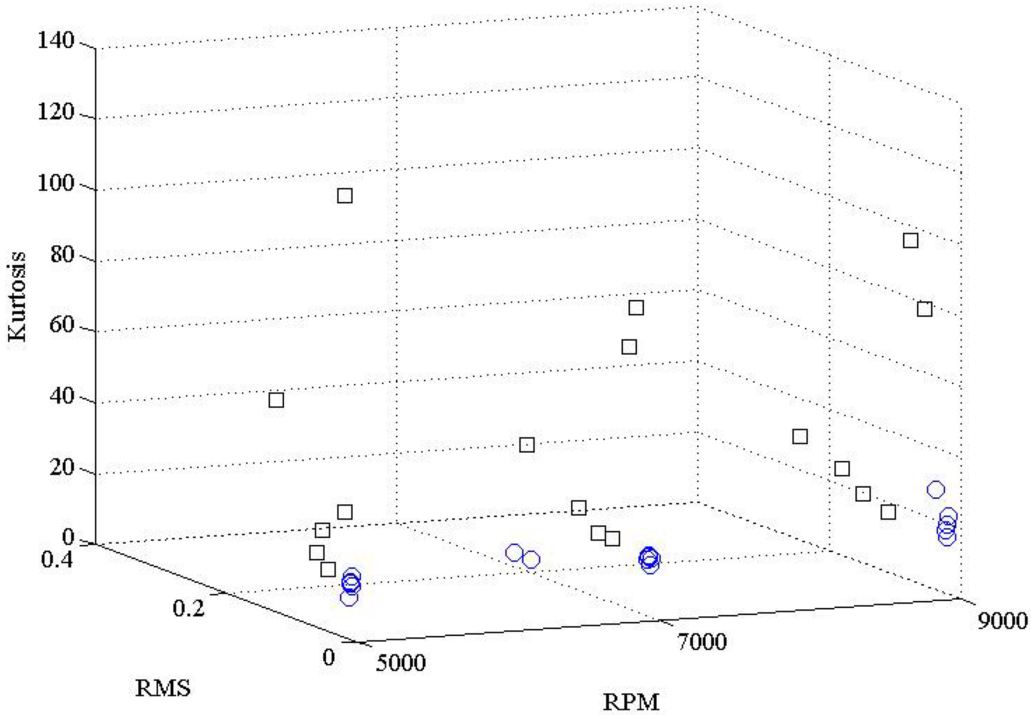

Figure 4. Kurtosis value of vibration data versus the hourly capacity of the machine

2.2 Definition of the output array

The output array of the net reflects the possible status of the bearing, that is a binary condition where 0 is supposed to be the healthy condition and 1 the faulted one. The net returns an output array which is a scalar value that usually could assume anyone of real values between 0 an 1. In order to force the output to be strictly in binary format, the result of the net will be rounded to the nearest integer, e.g. a result equal to 0.5 – that practically means the net doesn't recognise since it is just in the middle of the two extreme conditions – will be rounded to 1, i.e. the response of the net will be interpreted as “faulted bearing”. Although this action might seem strong, it follows the idea that the ANN has to be used as a decision making tool and then the greater or lesser propensity for a given result, implicitly excludes the other.

2.3 Split of training and testing data

The amount of data needed to train and test an ANN is well-known and controversial issue. There isn't a fixed role to set the optimal value or just the minimum value of data. Indeed a large number of input data allows the net to set its internal weight matrices on the basis of different cases. Moreover the data available have to cover both the training and testing step. In this paper the number of acquisitions available are equal to 35since 11 bearings have been tested at three different hourly capacity of the machine and 2 bearings at a single capacity. An arbitrary division of data into 70% for training step and 30% for testing step means about 24 and 9 acquisitions available respectively, which are not enough for the develop of an ANN.

In order to increase the input data the focus of the paper has been changed from the single acquisition of about 50 seconds to the single cycles performed by the machine during the acquisition time. With reference to third column of Table 1, e.g. the data regarding a single 3500 pph run have been split into 48 complete cycles, and each of them has been then considered as independent test. It must be considered that the presence of a non-stationary load afterward influences the vibration recorded on the motor in different manner cycle after cycle, strengthening the idea to consider each cycle as an independent acquisition.
After the split of the data the amount of cycles available is equal to 1680.
A further control has been made keeping away two bearings (one healthy at 7000 pph and one faulted at all capacities) from the amount of input data to the ANN. These acquisitions will be used to assess the capability of ANN as a diagnostic tool.

3. Results of the artificial neural network

The neural network used is a feed-forward, single hidden layer with 70 neurons. The transfer function used is the hyperbolic tangent sigmoid while the training function is based on the resilient back-propagation algorithm. The develop of ANN has been made by means of the Matlab Neural Networks Toolbox and then the final architecture is based on the choices offered in the software.
In particular different solutions of ANN have been tested and the optimal result came from the proposed architecture.
The training and testing steps have been characterized as follow:

- 11 bearings have been used
- The 31 acquisitions have been divided into 1488 data subset accordingly to the number of complete cycles of the machine.
- 70% of the data are used for training step, that is 1042 data.
- 30% of the data are used for testing step, that is 446 data.

The division of data between training and test has been made by choosing them randomly form all the set of acquisitions.
Figure 5 shows the result of the ANN in the testing step. The upper plot reports the real condition of the tested bearings, while the middle plot the classification of the ANN. Finally the lower plot states the quality of the ANN prediction. The results are promising since the is no error among all 446 data tested.
The suggested net has been applied to those two bearings deliberately kept away from the previous analysis. In particular:

- 2 bearings have been used
- The 4 acquisitions have been divided into 192 data subset accordingly to the number of complete cycles of the machine.

Figure 6 reports real status of the bearings, the classification of the ANN and its quality with reference to the 192 new data. The proposed ANN seems to correctly recognize the health of those two bearings and gives value to the use the ANN as a diagnostic tool in variable-speed applications.

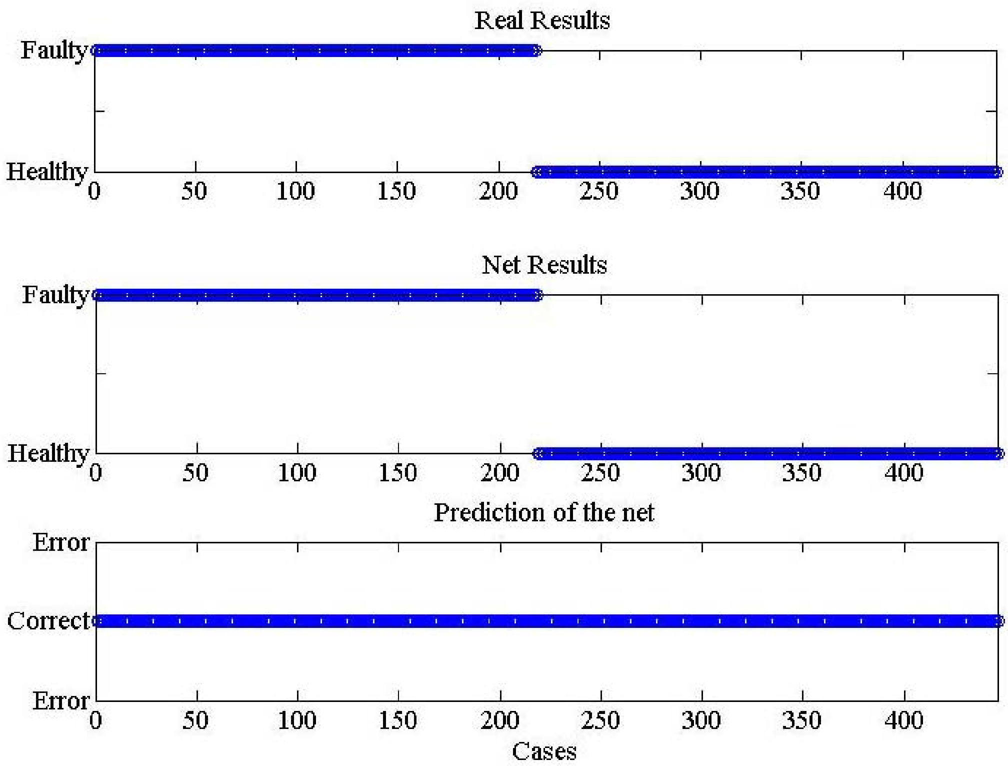

Figure 5. Testing step of the ANN: real condition of the bearings (upper plot), classification by the ANN (middle plot), quality of the ANN prediction (lower plot)

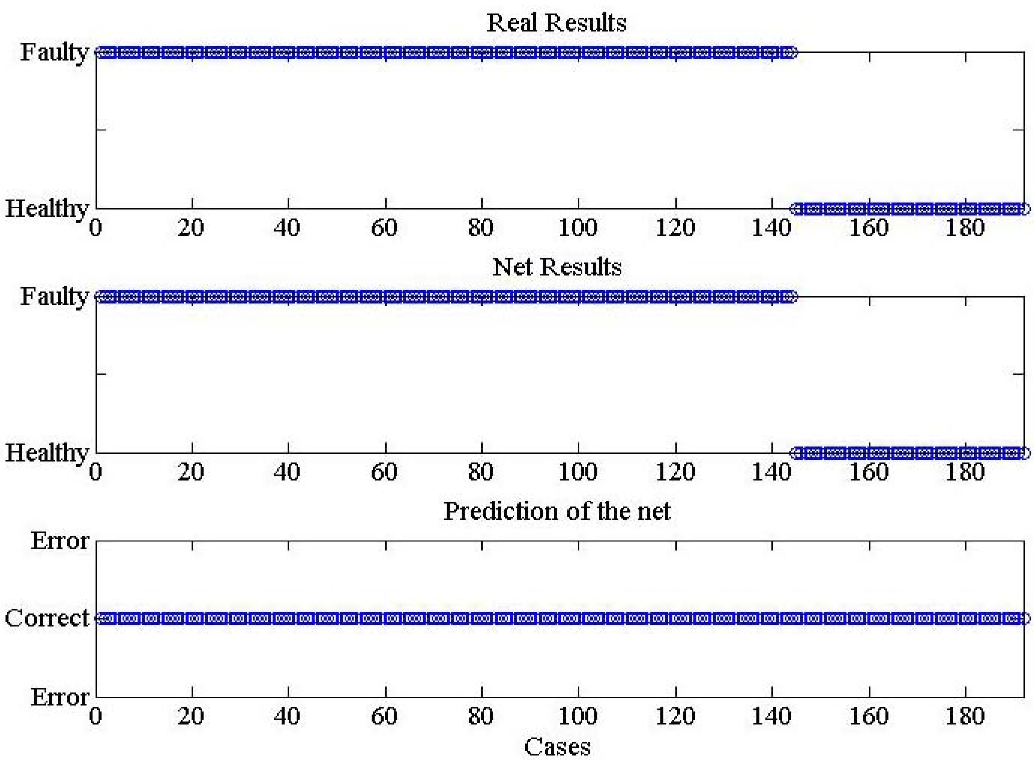

Figure 6. Testing step of the ANN: real condition of the bearings (upper plot), classification by the ANN (middle plot), quality of the ANN prediction (lower plot)

4. Conclusions

This paper reports the application of ANN as an automatic tool to diagnose the bearing health status in a practical industrial application. In particular the paper focuses on the condition monitoring of direct-drive motors. The peculiarity of these motors is that their motion law is fully programmable by the users thanks to the control system and an encoder mounted directly on board of the motor. Generally the position profile of the shaft follows a cyclic polynomial curve, that is the motor works with variable speed and with inversion of the rotation direction. From a diagnostic point of view, the rotational frequency of the motor changes continuously and it’s no more possible to identify the well-known fault characteristics frequencies of a damaged bearing.

This paper suggests the use of ANN as diagnostic tool to classify the bearings in two classes: healthy and faulted bearings. The input vector is a three-elements array made by the RMS value and the kurtosis of the vibration data, the nominal hourly capacity of the automatic machine the motor belongs to. The output is scalar value that can take two values: 0 for healthy condition or 1 for faulty condition. In order to increase the number of data available for training and testing purposes, the single acquisition of several seconds has been split in different single cycles of the machine. The neural network used is a feed-forward, single hidden layer with 70 neurons. The transfer function used is the hyperbolic tangent sigmoid while the training function is based on the resilient back-propagation algorithm. The net proved to be successful with complete recognition of the status of the bearings tested.

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