INTERNATIONAL JOURNAL OF COMPUTERS COMMUNICATIONS & CONTROL
Online ISSN 1841-9844, ISSN-L 1841-9836, Volume: 17, Issue: 3, Month: June, Year: 2022
Article Number: 4788, https://doi.org/10.15837/ijccc.2022.3.4788

Fault Detection in Three-phase Induction Motor based on Data Acquisition and ANN based Data Processing

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Abstract

The main objective of this paper is to investigate how a failure in the functioning of a normal electrical system represented by a three-phase asynchronous motor will modify the voltages and currents present in the system and if it is possible to design a system that is able to automatically detect the fault, based on the use of modern data acquisition system and powerful computer processing capabilities. The detection of faulty signals is realised using Feedforward Artificial Neural Networks.

Keywords: fault detection, feedforward artificial neural network, induction motor, parameter control, automated error detection.

1 Introduction

Three-phase rotating electric motors are widely used in industry in a large variety of applications from the simplest applications as conveyor belts to critical applications such as cooling pumps for the nuclear industry. The degradation of electric motors depends on the work environment (vibration, heat, moisture), load, duty cycle, and operation time [7]. Regardless of the application, the continuous operation of the electric motor is a key factor in any type of industrial application. The faults of electric motors can be categorized into two main categories, namely mechanical faults and electrical faults. The major mechanical faults are bearing faults [12] and broken rotor bar [19].

Different techniques are used in the monitoring of these electric motors and the determination of the faults of these machines. The main parameters being monitored for fault detection in electric motors are vibration data, temperature, acoustic signals, current, voltage, and other electrical parameters.

Vibration data acquisition is a frequently used technique as in [2, 4, 21, 26, 29, 30]. Using different data acquisition techniques (accelerometers or non-contact vibrometers) information regarding the vibration of the electrical rotating machine is acquired and then processed in order to determine the state of the components being analysed. This technique is effective in determining faults in the mechanical structure (bearings, rotor bar, fan).

Other techniques in monitoring the status of electric machines are based on monitoring electrical parameters such as voltage, current, phase [8, 23, 25]. This method is common and has the advantage of being easy to implement and the data acquired is directly related to the operation of the electric motor. The values obtained are processed in order to make a decision of whether there is a faulty or normal operation.

Temperature analysis is another technique used for electric motor fault detection and condition monitoring. Temperature is used either as a single parameter or in combination with other parameters [41]. Using the temperature has a disadvantage that it is not able to give an adequate indication regarding the localization of the fault or cause of it [37]. On the other hand, monitoring the temperature of the electric motor can indicate faults either in the mechanical structure (heating due to bearing faults) or in the electric part of the motor (degradation of stator windings).

Other monitoring systems rely on oil contamination analysis to evaluate the wear on the mechanical components [5], bearing analysis [31] or analysis of the acoustic emissions from the electric motors [27]. In [25] a fault detection system is presented for specifically determining the bearing outer-race defect at an early stage, which is one of the most common types of bearing defects.

Regardless of the method used to monitor the operating parameters of electric motors, it is necessary to process the data once it has been collected and to make a decision on the basis of this data, i.e. to modify the control system.

Various systems capable of processing the information obtained are used for decision-making. The main methods used are those based on Convolutional Neural Networks, Artificial Neural Networks. A Convolutional Neural Network (abbreviated as CNN) algorithm that can take a set of input data, assign importance to various aspects or characteristics in the data and be able to make a distinction between them. Such algorithms are used for fault determination for real-time monitoring [1], for bearings monitoring in electric motors [17, 36] or for fault detection based on vibration [16]. CNN is used also for processing signals with a significant noise component [32].

Artificial neural networks are computational networks used for data processing and decision making with large applicability in fault monitoring. In [18, 25, 28, 30] data regarding mechanical components (bearings) in electrical motors is analyzed using ANN. Non-mechanical data such as current, voltage, and vibration are also processed using ANN in order to detect faults in electric rotary machines [23, 24, 25, 39].

2 Artificial Neural Network (ANN)

Inspired by the data processing mechanism of the brain, Artificial Neural Network (ANN) is a well-established data mining method [43]. As an innovative tool, neural networks are used to predict events and statistical analysis [18]. Artificial neural networks have a high tolerance to noise and can adapt to changes in the data, so they are a good option to real-time fault detection [22]. Artificial Neural Networks are being applied in a vast number of fields such as in the energy field [14, 20, 33, 42], industry [6, 40] medicine and biology research [10, 38]. Also an important application of ANN is forecasting based on existing data [32]. This type of application is used in various fields such as supply and demand prediction models [3, 34],

Other fields of application of ANN are image processing [15], finance [3], management [9], education, engineering, trading.

2.1 ANN architecture

Artificial Neural Networks (ANN) mimic a biological neural network but they are significantly less complex as they are based on a lower number of connections and concepts [35].

Artificial Neural Networks have an individual structure inspired by biological nervous systems. As the structure of a brain, artificial neural network models are made up of artificial neurons in complex and non-linear forms. Neurons are connected to each other through weighted connections [13]. In figure 1, the most basic ANN can be represented as a collection of artificial neurons grouped in layers, with connexions between them.

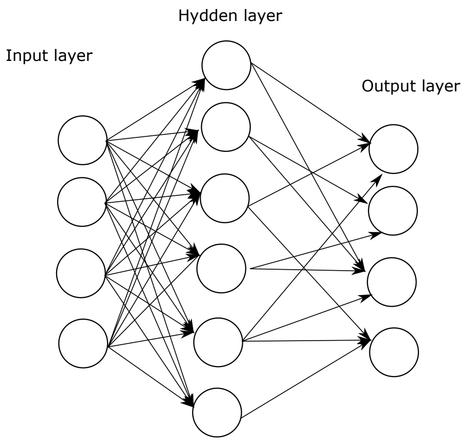

Figure 1: Simplified representation of an ANN

The first layer is the input layer of the ANN. This layer is responsible for sending data into the next layer or layers (depending on the ANN) called hidden layers. These layers will send data to the final layer called the output layer. Between the input and output layer, the inner layers are hidden and are formed by neuronal units which are adapting the information received from the previous layer using a series of transformations.

3 Experimental set-up

For the measurements a three-phase asynchronous induction motor was used (position 1 in figure 2), with nominal power of 3Kw, powered from the three-phase 3 x 240 VAC (position 2 in figure 2), mains, nominal frequency 50Hz, operating in idle, with nominal speed 1440 rpm.

In figure 2 the entire experimental set-up is presented.

The parameters acquired were the three supply voltages L_1, L_2 and L_3 and the absorbed currents I_1, I_2, I_2. For the data acquisition system, a DATA-Q INSTRUMENTS DI-2108 module was used (position 11 in figure 2). The system has 8 analog input channels with a 16-bit analog-to-digital resolution, a 160 kHz sample throughput rate, and also a full-scale range of ±10V.

For measuring the currents an interface to convert the value of the motor currents I_1, I_2, I_2 into a voltage signal in the range -10V DC ...+10V, which is the signal level accepted by the DAQ module inputs was used (position 14, 15, 16 in figure 2). For this interface, three Hall closed-loop current sensors HA2009 were used. The rated input is ±50A, rated output ±50mA, and auxiliary protection

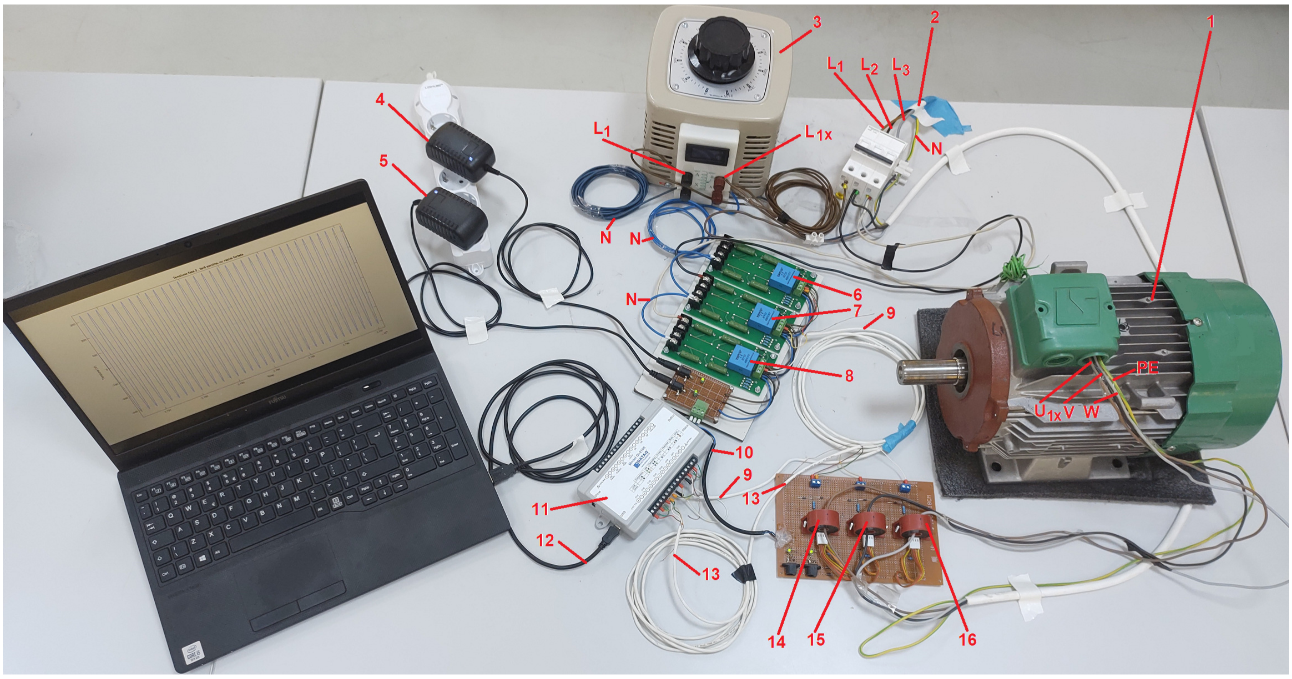

Figure 2: experimental sett-up for data aquisition

circuits were used. The choice of these sensors was made because they have an accuracy of 0.5%, linearity 0.2%, a bandwidth from DC to 150KHz AC and also a response time of $\leqslant 1\mu s$.

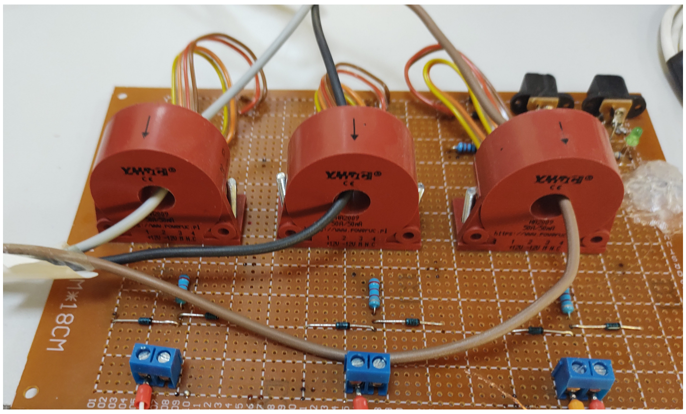

Figure 3: Hall closed loop current sensor HA2009

To measure voltages, a voltage interface was used, to transform the supply voltages from the 240Vac range supplied by the three-phase mains into a sinusoidal voltage in the range -10V ...+10V (position 6, 7, 8 in figure 2), which is the signal level accepted on the DAQ mode inputs. Three HV25 ±400V voltage sensors with rated output ±5V were used to realize the interface.

The chose of these sensors was made because they have an accuracy 0.5%, linearity 0.2%, and a very short response time of 40μs. The only disadvantage of these modules is the need to use two power supplies because the power supply is ±15V which was supplied by two SMPS voltage sources (positions 4 and 5 in figure 2).

In the experimental set-up, an autotransformer was used (position 3 in figure 2) in order to modify one of the voltage supply lines.

An electrical system when powered up at nominal parameters will absorb a current with a precisely defined waveform and electrical characteristics. In the case of an industrial system like the one presented in the above description, the system is supplied with three-phase symmetrical voltage systems which theoretically are identical. There is a tolerance accepted and guaranteed by the energy supply company, tolerances that are regulated in each country. Also, the motor has three identical circuits

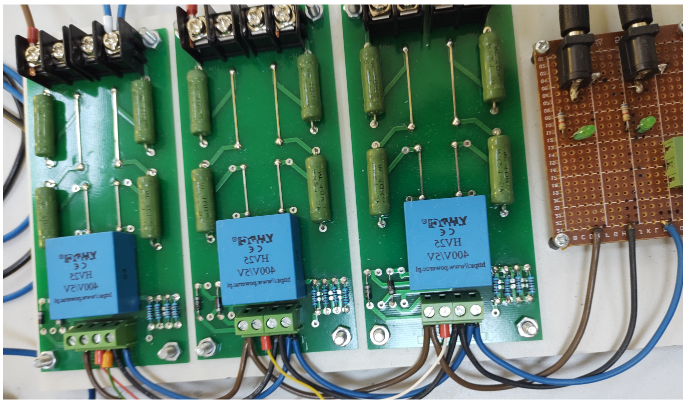

Figure 4: HV25 ±400V voltage sensors

(inductances) corresponding to each phase, but they also present a tolerance due to manufacturing technologies, that are accepted. As a consequence of this under normal functioning conditions, the supply voltages must be identical (with accepted tolerances) and also the three currents absorbed by the motor must be identical (with accepted tolerances).

Malfunctioning of the whole system can be caused by two major factors namely, a deficiency in the power supply system or a deficiency in the motor itself. Regardless of the type of malfunction accruing, it will cause an alteration of the currents signal (waveform, amplitude and phase, and so on). The most obvious sign will be the fact that the tree currents are not identical anymore and will be different compared with the currents under normal functioning conditions.

4 Experimental methodology

In order to achieve the objective of the paper, is necessary to determine how failures modify the signals present in the electrical system. The first step was to determine the normal condition operation of the electrical system and its tolerances. This was achieved by collecting a large set of measurements representing the normal operating conditions. These normal conditions were simulated by using the autotransformer and modifying one phase voltage at a time in small 2 V steps, in order to represent the normal situation where the supply voltage is in the accepted tolerance range. The large data set obtained is used as reference data for the normal operation of the system (in the accepted tolerance range.)

The next step was to simulate some failures in the system which must be detected as erroneous working conditions. For all situations, the acquired the signal data has a sample rate of 4ks/s for each signal.

4.1 Supply voltage unbalance

One of the most common situations is the unbalanced three-phase voltage system. Practically are simulated the following malfunctions using the autotransformer in the experimental set-up:

- Unbalance on L_1 , L_1 less with 30VAc than normal;
- Unbalance on L_1 , L_1 less with 50VAc than normal;
- Unbalance on L_2 , L_2 less with 30VAc than normal;
- Unbalance on L_2 , L_2 less with 50VAc than normal;
- Unbalance on L_3 , L_3 less with 30VAc than normal;
- Unbalance on L_3 , L_3 less with 50VAc than normal;

4.2 Contact resistance on one of the supply voltage lines

This type of fault is a common one in the industrial environment, due to corrosion of contacts, improper installation, and poore system maintenance. In order to simulate this fault, a resistor with values between 10Ω and 25Ω was mounted in series with the supply line.
The following faults were simulated.

- L_1 with 10Ω resistor;
- L_1 with 25Ω resistor;
- L_2 with 10Ω resistor;
- L_2 with 25Ω resistor;
- L_3 with 10Ω resistor;
- L_3 with 25Ω resistor;

4.3 Combined fault, supply voltage unbalance and contact resistance on one another supply voltage line

Another fault simulated was a combined one, where one of the voltage lines had an unbalance, and another voltage line had a contact resistor fault. The following combinations were made and the parameters acquired:

- Unbalance on L_1 , L_1 less with 30VAc than normal and L_2 with 10Ω resistor;
- Unbalance on L_2 , L_2 less with 30VAc than normal and L_3 with 10Ω resistor;
- Unbalance on L_3 , L_3 less with 30VAc than normal and L_1 with 10Ω resistor;

4.4 Combined error with an capacitor between supply line and ground and a series resistor on the same line

This fault is simulating a contact resistance on one power line and a parasitic leakage due to the deterioration of the insulation of one of the electric circuits. Measurements for the parameters of the following situations were made:

- Series resistor of 5Ω and $8\mu F$ capacitor on L_1;
- Series resistor of 5Ω and $8\mu F$ capacitor on L_2;
- Series resistor of 5Ω and $8\mu F$ capacitor on L_3;

5 Procedures of the proposed method

5.1 Data analysis

From all the acquired signals, 12 measurements of normal operating conditions and 12 measurements with the described faulty operation with 3 phases each, for voltages and currents, had been stored for analysis. In figure 5 is presented an example of acquired signals, the current signal on one phase for normal operation $I_1(1)$ and the current signal for phase one for faulty operation $I_1(25)$. As shown in the figure there is not a definitive characteristic to differentiate these two signals.

In order to identify a feature or characteristic that can differentiate the two signals, the power spectrum of the analyzed signals was computed. In figure 6 is presented the power spectrum for the signals presented in figure 5.

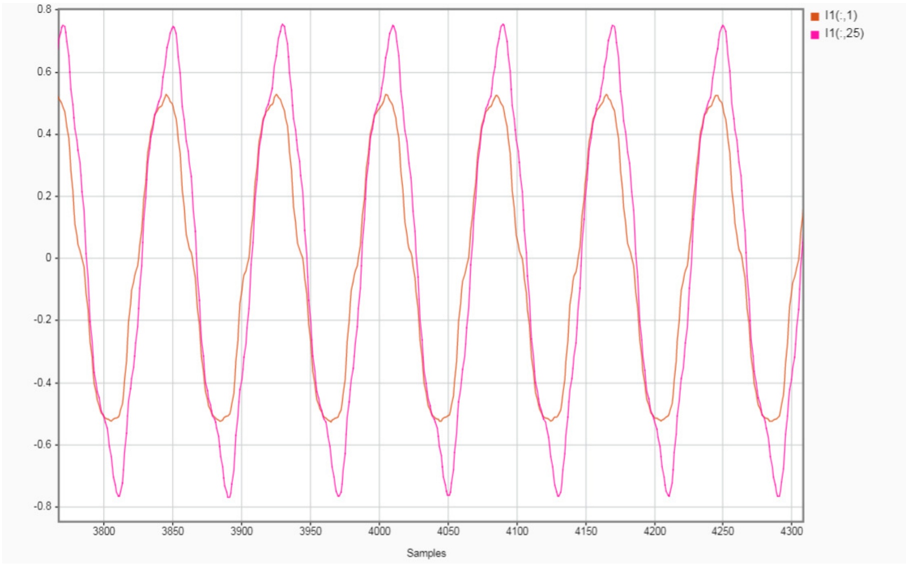

Figure 5: Current signal on phase L_1 for normal operation $I_1(1)$ versus Curent signal on L_1 $I_1(25)$ for faulty operation

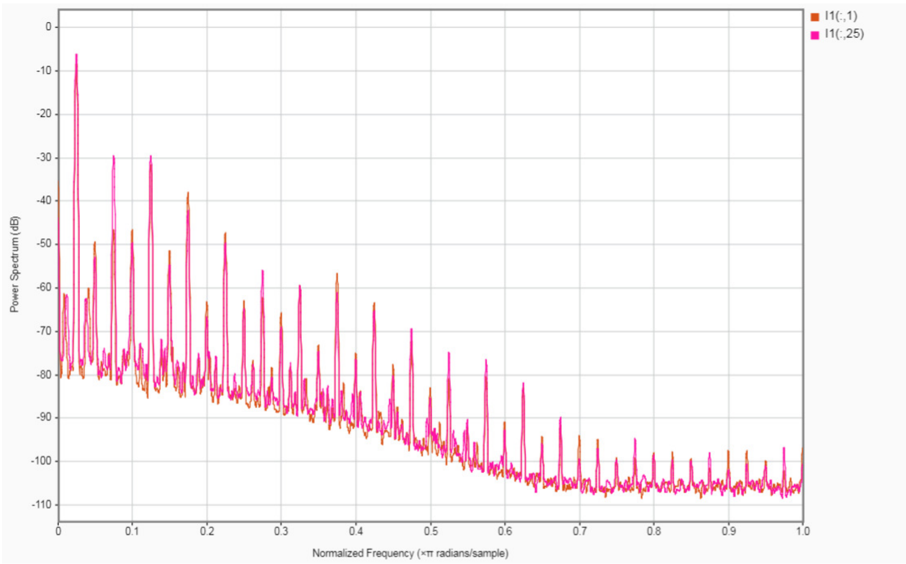

Figure 6: Power spectrum of signal presented in figure 5, current signal on phase L_1 for normal operation $I_1(1)$ versus current signal for phase L_1 for faulty operation $I_1(25)$

Studying the Power Spectrum of the acquired signals (figure 6), it is possible to observe that there are differences in peeks frequencies of specific harmonics as it is shown in the details in figure 7. These differences are consistent with the defect type and had to be observed for each one specifically.

In our case, the 3 phases for each measurement amplitude had to be normalized in order to have a better representation of the signals. These are presented in figures 8, 9, and 10. The peaks drawn with black correspond to normal operation, while the ones with red correspond to faulty operation.

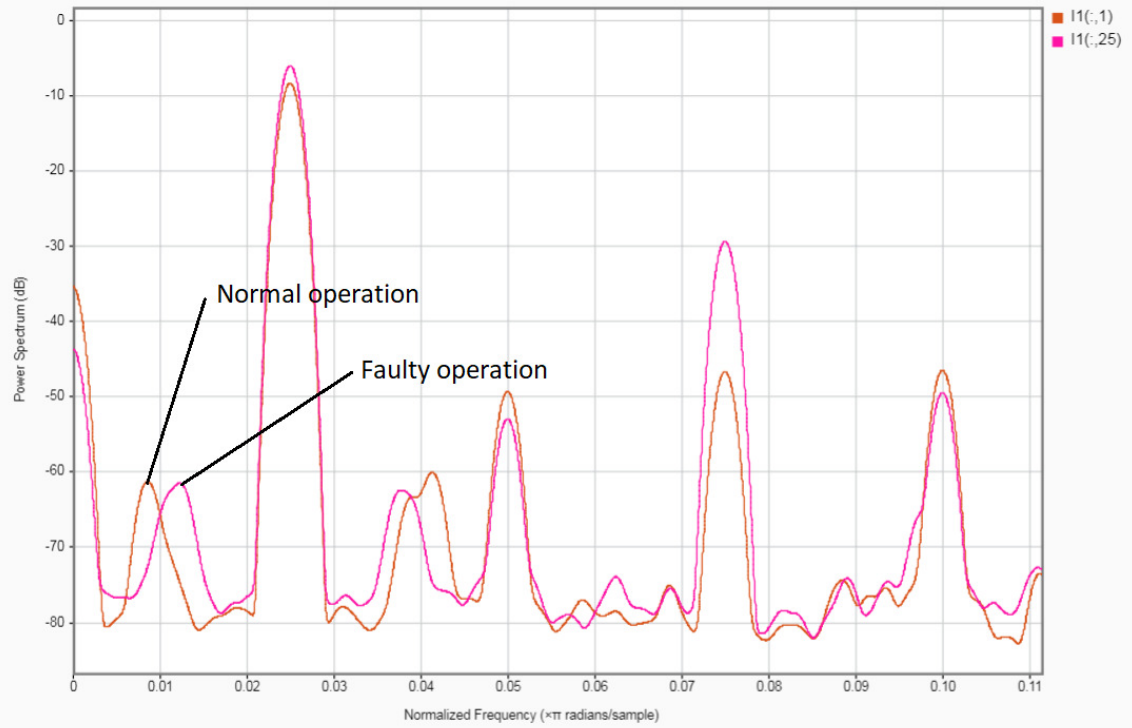

Figure 7: Detail of power spectrum presented in figure 6 between 0 and 0.02 rad/sample

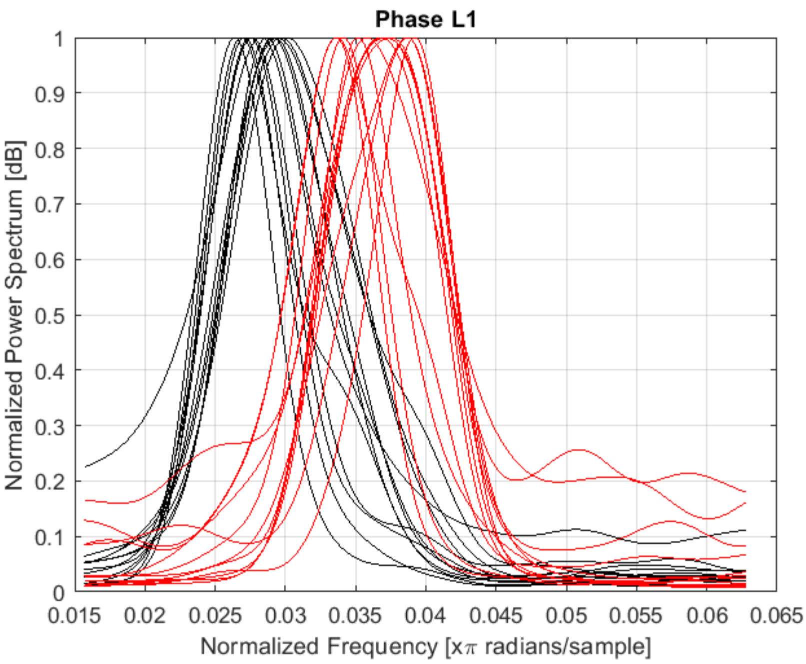

Figure 8: Power spectrum details for 12 normal operation current signals and for 12 faulty operation current signals - phase L_1

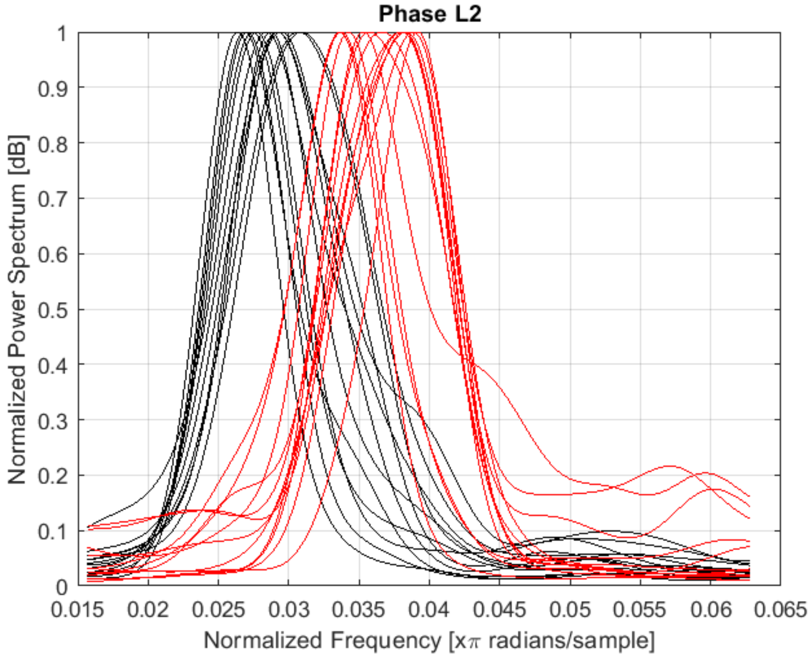

Figure 9: Power spectrum details for 12 normal operation current signals and for 12 faulty operation current signals - phase L_2

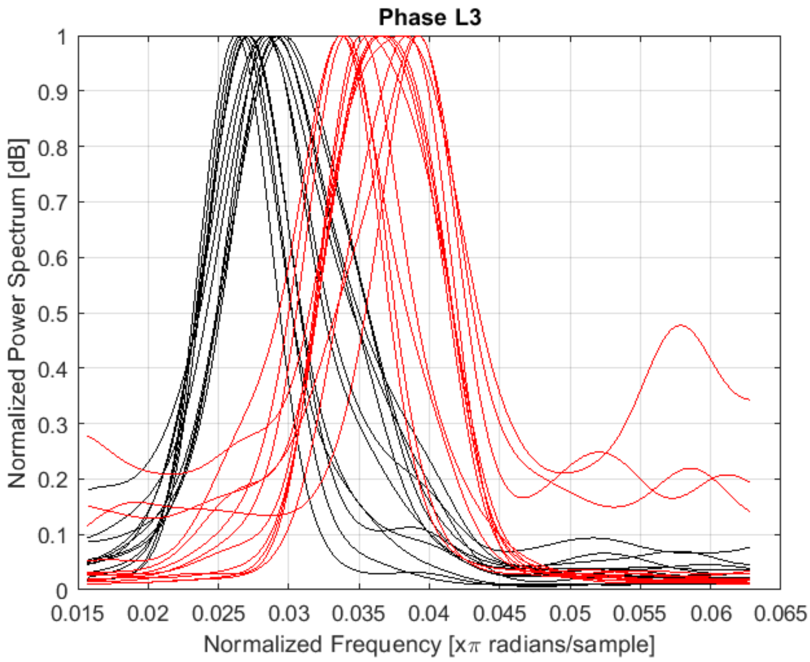

Figure 10: Power spectrum details for 12 normal operation current signals and for 12 faulty operation current signals - phase L_3

5.2 Signal classification using a feedforward artificial neural network

In order to automatically distinguish between the normal and faulty operation signals, a feedforward artificial neural network is employed. For this purpose, the MATLAB development platform and the Machine Learning and Deep Learning (nprtool module) was used. The Neural Pattern Recognition toolbox employs a two-layer feedforward network, with a sigmoid transfer function in the hidden layer and a softmax transfer function in the output layer [11].

The network structure has 4096 inputs, 10 hidden layer neurons, and 2 output neurons and is presented in figure 11. The training data consists of 72 samples, each of 4096 elements, half of them representing normal operation and the other half faulty operation signals. These samples have been divided into training (70%), validation (15%), and testing (15%). The number of output neurons must be equal to the number of elements in the target vector, which is the number of categories of the classification process. In our case, there were two categories: normal operation of the electric motor or faulty operation of the electric motor.

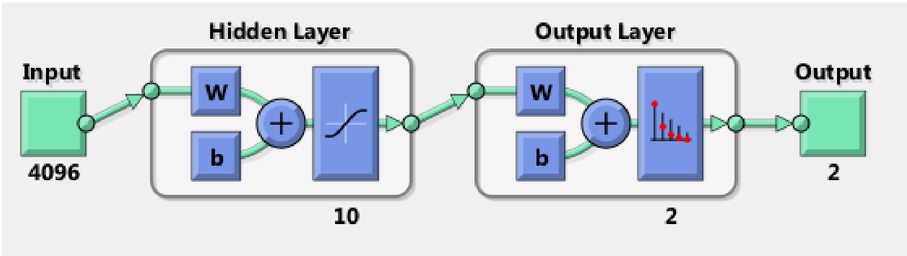

Figure 11: Network structure

Following the training of the network, the results obtained are shown in figures 12, 13 and 14.

The training performance diagram for the artificial neural network (ANN) is presented in figure 12. As it can be seen for train, validation and test, a very small error had been achieved in 62 epochs.

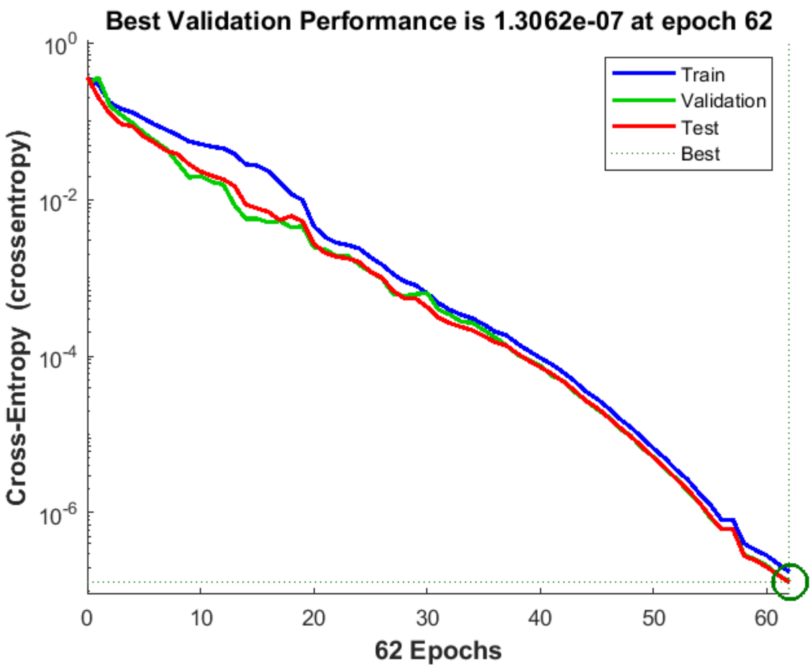

Figure 12: Error diagram, evolution of errors versus training epochs

In figure 13, the results of a successful testing session is presented in the form of a confusion matrix. In this representation, each column of the matrix represents a predicted class, while each row represents a true class. The green squares represent the correctly classified and the red squares represent the incorrectly classified samples. As can be seen in the confusion matrix, each sample, for this case, was correctly classified.

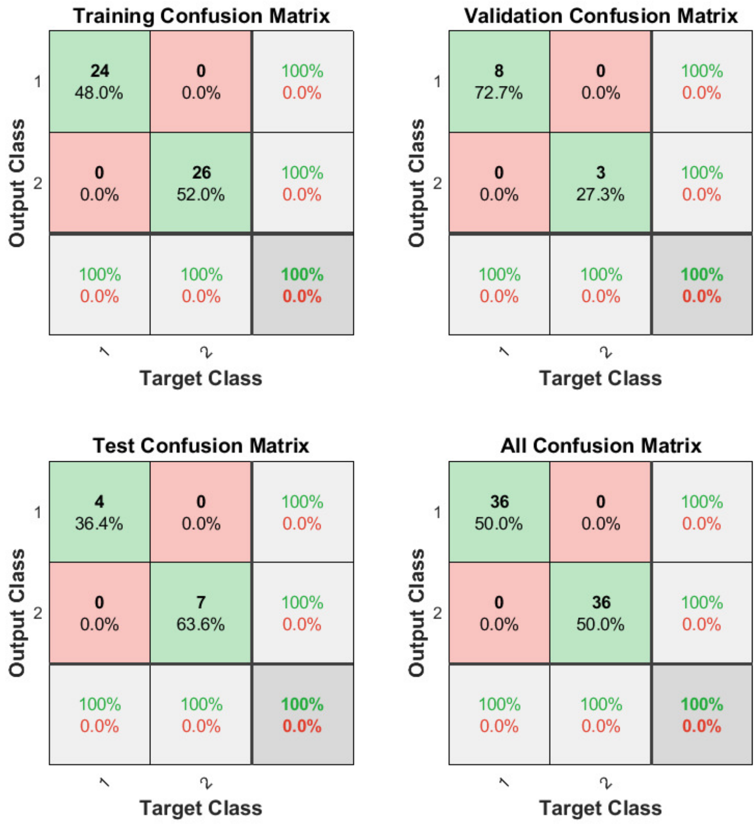

Figure 13: Confusion Matrix

In figure 14 the error histogram of the Artificial Neural Network is presented and it represents the histogram of the errors between target values and predicted values after training the feedforward neural network. The errors in the trained ANN are divided into 20 bins. As presented in the figure majority of errors are classified in the bins closer to zero.

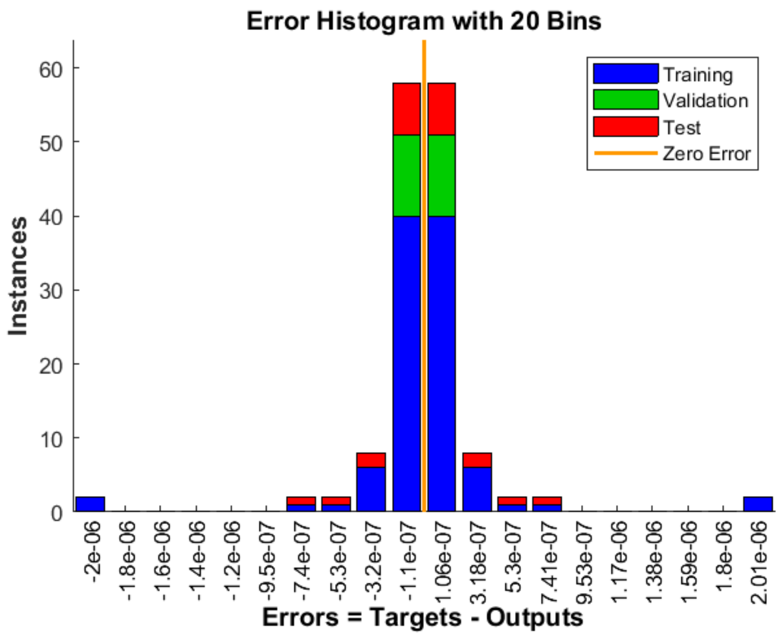

Figure 14: Error histogram

6 Conclusions and future work

The main goal of the research was to identify and classify the influence of several types of faults on the electric parameters in an electric circuit, namely in a three-phase electric asynchronous motor. To achieve this a large number of faults were simulated. A detailed explanation of the simulated faults is presented in chapter 4.

Main faults were related to the unbalanced supply voltage on one of the phases, simulation of leakage on one circuit, and contact resistance. For all these simulated faults data was acquired alongside data corresponding to normal operation. After realizing the data collection the data were analyzed in order to identify the markers of specific faults in the signals acquired.

In the power spectrum of the acquired signals, in the normalized frequency interval of 0 and 0.02 radians/sample, a shift in harmonics between the normal operation and faulty operation signals was identified. Based on this data analysis we generated and successfully trained a feedforward artificial neural network. The network has a low error and high success rate in identifying faults related to contact resistance and unbalanced supply voltage.

The next step in developing the system is related to the classification of errors. The system presented in this paper has only two outputs. This means that the system can only classify the input signals as corresponding to normal operation or faulty operation. The next step should develop the ability of the system to not only determine that a signal corresponds to a faulty operation, but also be able to classify the types of errors.

Funding

The research has been funded by the University of Oradea, within the Grants Competition "Scientific Research of Excellence Related to Priority Areas with Capitalization through Technology Transfer: INO - TRANSFER - UO", Project No. 326/21.12.2021.

This project is funded by the Romanian Ministry of Research, Innovation and Digitisation through Programme 1 - Development of the National Research and Development System, Subprogramme 1.2 - Institutional Performance - Projects for funding the excellence in RDI, Contract No. 29 PFE / 30.12.2021 with University of Oradea.

Author contributions

The authors contributed equally to this work.

Conflict of interest

The authors declare no conflict of interest.

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Cite this paper as:

O.G. Moldovan, R.V Ghincu et al. (2022). Fault detection in three phase induction motor based on data aquisition and ANN based data processing, *International Journal of Computers Communications & Control*, 17(3), 4788, 2022.
https://doi.org/10.15837/ijccc.2022.3.4788