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# Induction motor failures detection using Motor Current Signal Analysis (MCSA) and two-step Support Vector Machine (SVM) classifier

***Abstract**. The induction motor, because of its robustness, is very widespread in the industrial environment. Its use is firstly at the training of non-variable speed systems. Today, with the improvement of the power electronics, the asynchronous motor can be servo-controlled both in torque and speed. The asynchronous machine is no longer limited to constant speed applications. It is therefore found more and more in electric traction, but also in electromechanical actuators which require a control in position and for which this type of engine was not previously usable, but it is not immune to several anomalies in the industrial field, such as breaks in bars, short circuits, misalignment. So then this article enters the diagnostic framework, through the use of the SVM formalism for the localization of electrical faults in induction motor. This study is based on the stepwise application of the SVM, firstly, the nature of the fault (break of bar or short circuit of turns in the phases of the stator) is compared with the normal behavior of the asynchronous machine, this step requires the use of the SVM one against one (One vs. One). Secondly we consider the fault detected by the first analysis and try to rank it and classify it among different classes of faults of the same nature, which can give a degree of severity a reliable decision to maintenance expertise. It uses the technique of one against all (One vs. All). The proposed approach is based on the use of feature extraction especially the amplitudes and frequencies, reflecting the behavior of the induction motor, using the Motor Current Signal Analysis (MCSA); then the classification of these characteristics is realized by SVM method. The SVM classification is conducted on a 1Kw induction machine experimental benchmark with different faulty operating conditions.*

***Streszczenie.** Silnik indukcyjny, ze względu na swoją wytrzymałość, jest bardzo rozpowszechniony w środowisku przemysłowym. Jego zastosowanie to przede wszystkim trening systemów bez zmiennej prędkości. Obecnie, wraz z udoskonaleniem elektroniki mocy, silnik asynchroniczny może być sterowany serwomechanizmem zarówno pod względem momentu obrotowego, jak i prędkości. Maszyna asynchroniczna nie jest już ograniczona do zastosowań o stałej prędkości. Dlatego coraz częściej znajduje się w trakcji elektrycznej, ale także w siłownikach elektromechanicznych, które wymagają kontroli położenia i dla których ten typ silnika nie był wcześniej używany, ale nie jest odporny na kilka anomalii w dziedzinie przemysłu, takich jak pęknięcia prętów, zwarcia, niewspółosiowość. Tak więc ten artykuł wchodzi w ramy diagnostyczne, poprzez wykorzystanie formalizmu SVM do lokalizacji uszkodzeń elektrycznych w silniku indukcyjnym. Niniejsze badanie opiera się na stopniowym stosowaniu SVM, po pierwsze, charakter usterki (przerwanie szyny lub zwarcie zwojów w fazach stojana) jest porównywany z normalnym zachowaniem maszyny asynchronicznej, ten krok wymaga użycia SVM jeden na jednego (jeden na jednego). Po drugie, rozważamy usterkę wykrytą podczas pierwszej analizy i próbujemy ją uszeregować i sklasyfikować wśród różnych klas usterek o tym samym charakterze, co może dać pewien stopień dotkliwości ekspertom w zakresie konserwacji. Wykorzystuje technikę jeden przeciwko wszystkim (jeden przeciwko wszystkim). Proponowane podejście opiera się na wykorzystaniu ekstrakcji cech, zwłaszcza amplitud i częstotliwości, odzwierciedlających zachowanie silnika indukcyjnego, z wykorzystaniem analizy sygnatury prądu silnika (MCSA); wówczas klasyfikacja tych cech jest realizowana metodą SVM. Klasyfikacja SVM jest przeprowadzana na doświadczalnym wzorcu porównawczym maszyny indukcyjnej o mocy 1 kW z różnymi wadliwymi warunkami pracy. (**Wykrywanie awarii silników indukcyjnych za pomocą analizy sygnału prądu silnika (MCSA) i dwuetapowego klasyfikatora maszyny wektorów nośnych (SVM)**)*

**Keywords:** Diagnostic, induction motor, MCSA, SVM.
**Słowa kluczowe:** Diagnostyka, silnik indukcyjny, MCSA, SVM.

## Introduction

Today, the industrial world uses increasingly specialized and complex processes as well. For manufacturers, to guarantee good operation and reduce unavailability period after a fault have become capital issues. Focusing on induction motors use to achieve their goals, and due to their reliability / cost / efficiency ratio, induction motors have become an essential tool in industry for conversion of electrical energy into mechanical energy. Therefore, their diagnosis is a major requirement to increase processes availability including use of techniques and methods designed to detect anomalies that differ from normal operation [1,2].

Thus, one of the most important aspects of power system planning and operation is the design of protection systems that manage faults monitoring and detection. Engineers design protection systems to eliminate safely faults in the power system [3,4]. Since then, faults monitoring and detection in electrical machinery have evolved in recent years from traditional techniques to artificial intelligence (AI) techniques. Such techniques require "minimal configuration intelligence" because there is no need neither for detailed analysis of the fault mechanism nor for system modelling.

When we use an AI technique already used, faults detection and evaluation can be performed without an expert. Some work has also been carried-out on induction motor drives powered by a converter to achieve a fault-tolerant drive to prevent shutdown when load conditions are satisfied, as well as failures [5].

The most known KERNEL's method is SVM form that was inspired from Vapnik's learning statistical theory. The SVM is a method of binary classification via supervised learning [6]. This method relies on the existence of a linear classifier in suitable space acting by a two-class method, uses a set of training data to learn the model parameters. It is based on the use of the called '' KERNEL'' functions that allow optimal data separation.

It induces searching for a hyper-plane to separate data sets (classes). It has shown good performance for solving various problems [7]. This technique has proven effective in many application areas, such as image processing, text categorization or multimedia diagnostics. Even on very large datasets, its choices are most often made via a validation way in which system performance is estimated through understanding it from examples that were not used during learning process. . The idea is to seek for parameters allowing maximum performances.

Actually, diagnostic technology for rotating machinery, such as induction motors, is still growing rapidly. Upon fault, it affects the machine dynamic conditions such as vibration, sound, temperature, etc., and can be a very useful detection indicator. Based on these symptoms, many diagnostic methods are used as the Support Vector Machine (SVM) [8].

**Experimental data acquisition**

Experimental tests are carried-out in our LGEA laboratory. Samples were acquired via test bench provided with a DSPACE 1104 board, the main processor is an MPC8240, whose internal clock is at 250 MHz, and the measurable quantities are acquired over a 10 second interval with a frequency sampling of 10 KHz for a number of 100,000 points. A set of measurement data includes 47 samples for different cases of induction motor. Tests were carried-out in healthy engine case for various loads using a magnetic powder brake in a range of (0%, 25%, 75% and full load), then 05 tests regarding short-circuit between turns of 09 turns (2%), 18 turns (4%); 27 turns (6%), 36 turns (8%) and 54 turns (10%) for one phase and two phases with no-load. Then, tests for one broken and two broken bars are carried-out on our motor for different load values.

Upon data acquisition within time domain, we use Fast Fourier Transform FFT to perform analysis in the spectral domain. Experimental tests were carried-out on a cage induction motor of 1.0 KW power, with star windings, Δ / Y = 220/380 V rated voltage, Δ / Y = 3.8 / 2.2 A, cos (φ) = 0.83 rated current, 2880 rpm nominal speed and number of pole pairs = 1.

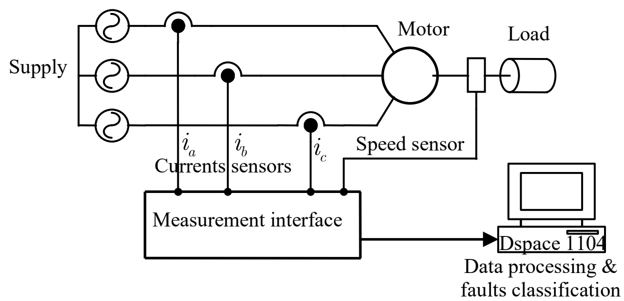


Fig.1. Diagnostic system block diagram

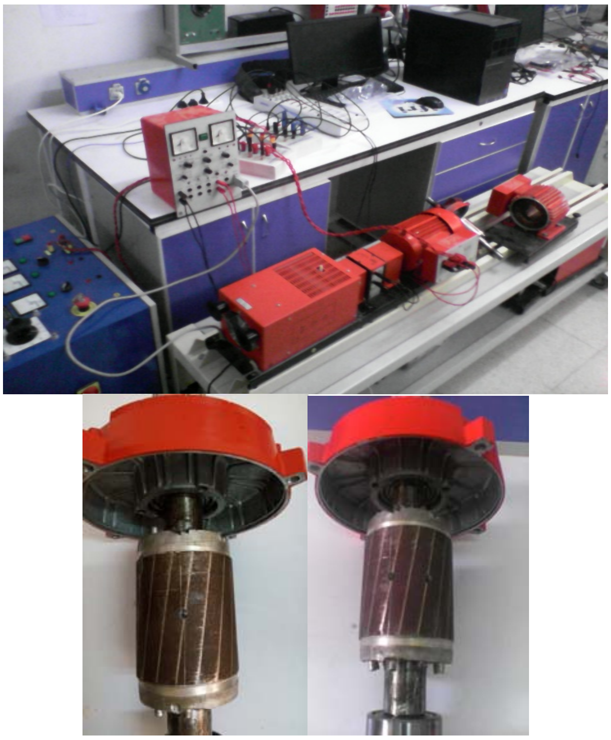

Fig.2. Test bench at LGEA Laboratory

**Analysis of induction motor fault with MCSA**

MCSA technique best advantage is that it reduces to minimum the sensors number compared to vibratory tests [9-12]. In most cases, use of this method can be divided as follows:

- Breaking of bars and rings.
- Faults of stator (opening or short-circuit of turns inside stator phase windings).
- Static and/or dynamic failures of the air-gap.
- Anomaly of the induction motor supply.
- Dynamic or static eccentricity that can cause friction between rotor and stator core, causing severe damage to the stator and its windings.
- Bearing faults subjected to mechanical vibration, overload misalignment, current fluctuations, corrosion and poor lubrication.

The MCSA monitors the motor stator current (especially the supply current). A single stator current is used for monitoring instead of the three phases of the motor supply current. The motor stator windings are used as sensors in the MCSA, that recover the signals (induced currents) from stator (but also provide data about the rotor condition) [13]. In fact, stator current form is rich in harmonics reflecting the induction motor status but not automatically meaning faults. Ideally, the motor current should be a pure sinusoidal signal.

In our experimental study, we focused on the standard stator and rotor faults related to half of the anomalies only that are present in the induction motor faults (especially the stator windings short circuits) and rotor typical faults with bar breaking.

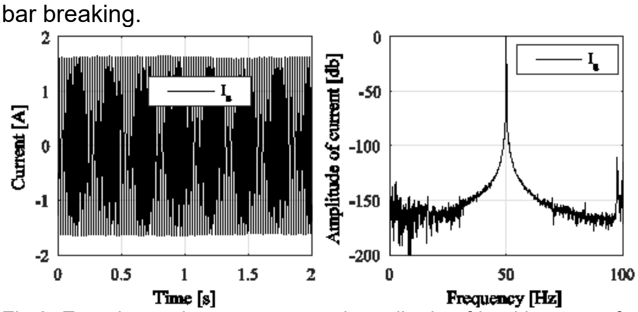


Fig.3. Experimental appearance and amplitude of healthy motor for no load.

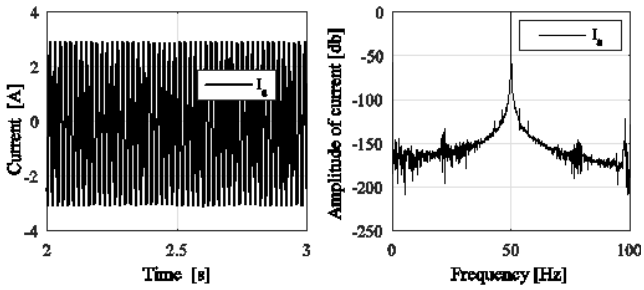


Fig.4. Experimental appearance and amplitude for loaded healthy motor.

Therefore, spectral analysis has become very successful for manufacturers since it is the most economical and fastest method of diagnosis. However, this method is only suitable for constant speed diagnostics and mainly on machines connected to the power supply. Thus, spectral analysis control of the induction motor consists in performing a simple Fourier transformation of the quantities affected by the fault and in visualizing the parasitic frequencies that represent the machine fault signature. The selected quantities are the electrical quantities (in particular the line currents) [14-15].

**Analysis of healthy motor cases**

The motor operation spectral analysis shows the fundamental harmonic frequency *fs = 50* Hz and the current amplitude increases as the machine is loaded (Figures 3, 4) which it is influenced by the actual power network connection and which will have an impact on the diagnosis.

**MCSA Analysis of short-circuit currents: case of short circuit between turns**

The main aging factor is the abnormal warming of the coils. For machines operating in hostile environments, settling of dust and moisture can weaken the electrical isolation and short-circuiting the stator windings.

The short circuit turns is the most harmful fault and the most frequently encountered in the stator. Indeed, the current flowing in the short-circuit turns is ten times higher than the nominal current.

Upon short-circuit, vibrations and torque oscillations occur that reveals presence of new components in the torque and consequently in the stator current [17-18].

Figure 5 shows short-circuits influence between phase A turns timed from the fault application for a value of 6% on the low-load three-phase motor current transactions. This increases the current as the number of short-circuit turns increases during the fault phase, while even the other two phases are affected by this fault despite the motor commutation (three-phase balanced direct system),

This increase is explained via the stator winding change, implying a variation of the phase inductance affected by the fault and impacts the other phases by magnetic coupling. In contrast, the currents pace remains unchanged.

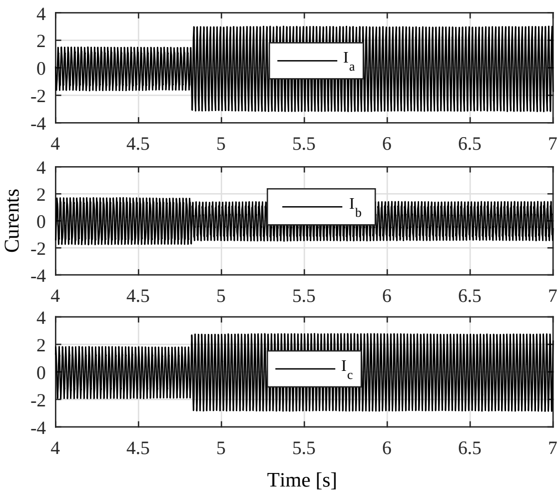


Fig.5. Phase currents during a 6 % short circuit on A-phase

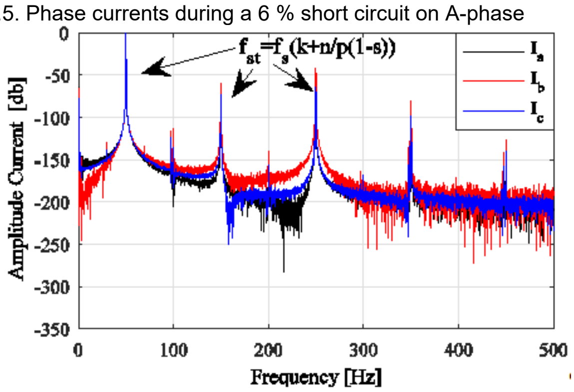


Fig.6. Spectral analysis of 6 % short circuit current on A-phase

Figure.6 Presents the spectral analysis of the 6% experimental short-circuit model in phase A, showing the appearance of the new harmonics at multiple frequencies of the first harmonic $f_{st}$ (150 250 350 ...), that verifies the formula.

(1) $$f_{st} = f_s\left(k \pm \frac{n}{p}(1-s)\right); n = 1, 2, 3$$

$f_{st}$ is the component related to shorted turn

Thus, increasing of harmonics amplitudes is proportional to increasing of faulty turns numbers.

**Analysis of currents in case of broken bar**

Typical faults of induction motor rotors are due to a manufacturing fault or misuse, in particular [19]:

- Partial or total failure of a rotor bar(s), generally caused by loads heating.
- Resistive bar due to air pockets presence in the rotor grooves and notches. This fault occurs during manufacture.
- Weld break at the short-circuit ring, especially for high power.
- Possible pronounced eccentricity of the rotor.
- Premature or unintentional damage of bearings (wear of ball bearings) which often leads to machine performance change.

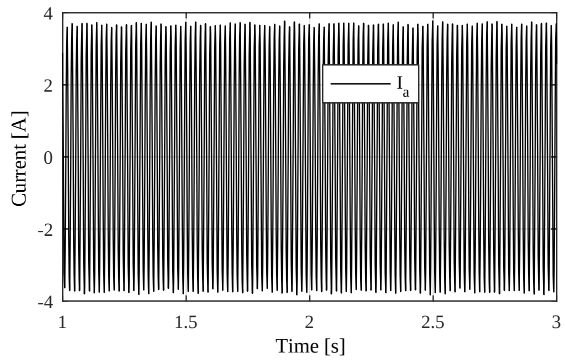


Fig.7. Phase-A current amplitude for one broken bar at full load

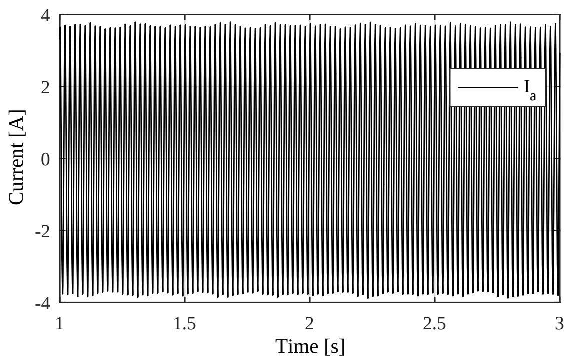


Fig.8. Phase-A current amplitude for two broken bars at full load

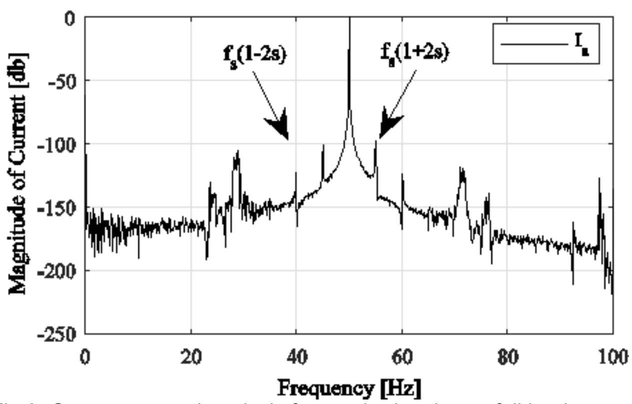


Fig.9. Current spectral analysis for one broken bar at full load.

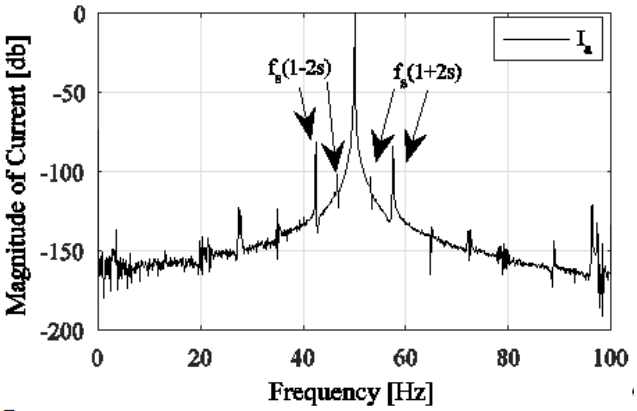

Fig.10. Current spectral analysis for two broken bars at full load

Note that stator current amplitude appears in presence of broken bars. This modulation increases as the broken bars number increases and appears more significant under load effect [figures 7,9].

Appearance of broken bar fault [Figures 8,10] causes increasing of some lateral components (harmonics) amplitude related to the fundamental $f_s = 50\,\text{Hz}$ and whose frequencies correspond to [19].

**MCSA Analysis of short-circuit currents: case of short circuit between turns**

The SVM is designed for binary classification problems, assuming that data are linearly separable. It may be required to transform the inputs to process them more easily, $xi$ : is any space between the inputs.

We transform the inputs into vectors in a space $F$ (characteristic space) by a function: $\Phi : xi \rightarrow F$, where $F$ is a sub-dimension of Hilbert space.

Given the learning data $(xi, yi), i = 1,\dots,l, xi \in R_n, yi \in \{+1,1\}$, where $R_n$ represents the input space, $xi$ the sample vector and $yi$ the characteristics class. Therefore, we choose the optimal hyper-plane that properly classifies the data (when possible) and which is as far as possible from all the points to be classified. So, we must have a maximum range [20-21]

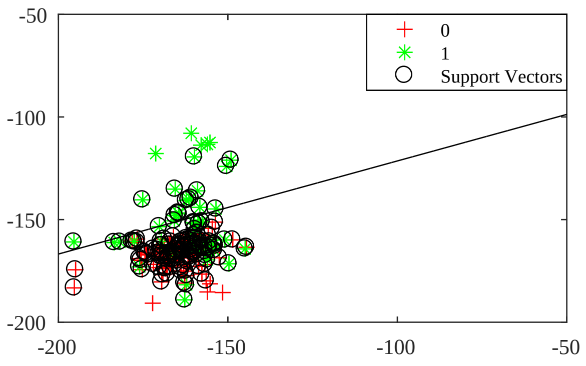

Fig.11. Example of SVM space using two class fault characteristics.

In practice, we use KERNEL functions:

- Linear $k(x, y) = x.y'$
- Polynomial $k(x, y) = (1 + xy)^d$
- Gaussian (RBF) $k(x, y) = e^{-\frac{\|x-y'\|^2}{\sigma}}$
- Multi-Layer perceptron (Mlp)

$k(x, y) = \tanh(p_1 xy' + p_2);\ p_1 > 0$ and $p_2 < 0$.

In technical literature, the most used KERNEL functions are the linear, quadratic, polynomial and Gaussian (RBF) (radial basis function). However, by using polynomial nuclei and RBF, it is possible to build any hyperplane, which can be defined by linear or quadratic KERNEL [20].

SVM can handle large data intervals, making it the most efficient diagnostic solution, significantly predicting various faults and providing a quick response to faults and consequently, reducing maintenance costs. Due to its versatility, and its KERNEL function types used regarding parameter specification, SVM is very well suited to different types of input data [5]. To diagnose the anomalies, the experimental measurement characteristics using MCSA (particularly, magnitude and frequency that locate the fault) will be inserted in a plane of n dimensions, while the found hyper-plane should determine the sample class.

The motivation of this work lies in the achievement of a classifier that will rank efficiently the various motor faults i.e. bar breaks and short-circuits between turns (cases of our study).

Our diagnostic process consists of detecting the fault nature regarding the reference data on the motor characteristics via the One-vs-One method, then to classify the fault extent according to its nature (fault gravity)

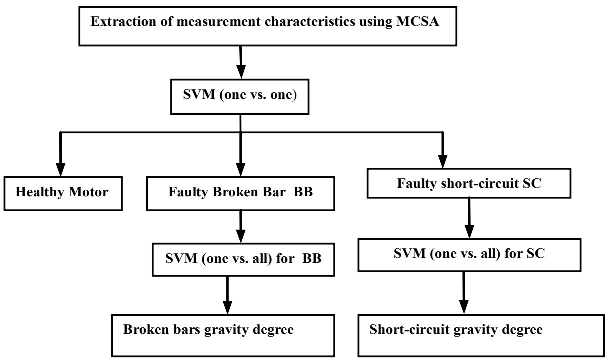

Fig.12. Current Strategy for using two-steps SVM

**Use of "One-vs.-One" strategy**

The one-vs.-one strategy aims to build an SVM for each pair of classes. Thus, for a problem with c classes,

n (n-1) / 2 SVM are designed to differentiate samples from one class to another class. Generally, classification of an unknown sample is made according to the maximum selection, where each SVM is chosen for a class [5,20].

**Influence of KERNEL functions on the classification**

There are no rules in the choice of the KERNEL function; generally, it depends on the perceived problem. In this case, the KERNEL function impact is studied, the SVM (One-vs.-One) is built to identify the fault nature. This is only allowed via using all the data of the machine same state (Healthy, turns short-circuits and bar breaks).

One-vs.-One test is used only to detect the fault nature or, if required, to classify two samples of the same nature. [21-22]. The first test is used to detect the healthy state of the other faults, then to view the fault type, regardless the normal state or the other fault condition. All this by using the most common KERNEL functions i.e. linear radial basis, RBF Gaussian function, polynomial and sigmoid (MLP), to compare the most optimal Cp class performance of these functions.

In Figures 13,14,15, SVM application with the RBF function in different cases allowed us to note that coefficient of performance is about Cp = 0.9867 (98.67%); for Figures

16,17,18, use of SVM with Polynomial function in a chosen order between (1 <n <6) led us to a maximum coefficient of performance of Cp = 1 (Cp = 100%); for Figures 19,20,21, use of SVM with MLP function of [-1; 1] arbitrarily chosen, showed us that coefficient of performance is Cp = 0.88 (88%), Cp = 0.86 (86%) and Cp = 0.866 (86.6%) respectively for different cases of induction motor operation. The following figures show RBF results with different motor states:

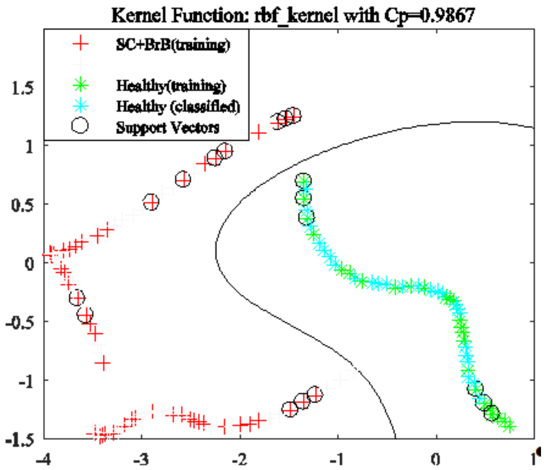

Fig.13. RBF for healthy motor (Cp=98.67%),

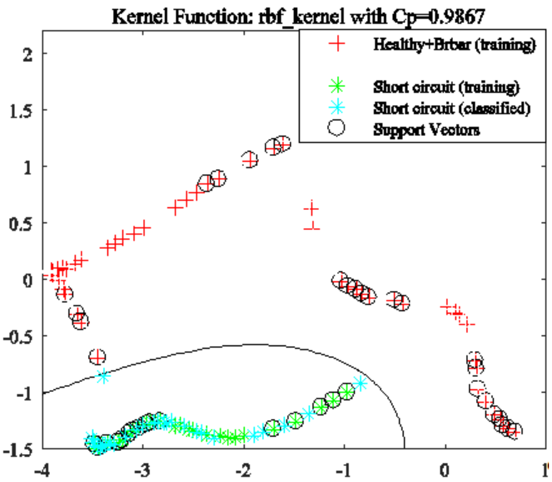

Fig.14. RBF for short circuit interturn (Cp=98.67%),

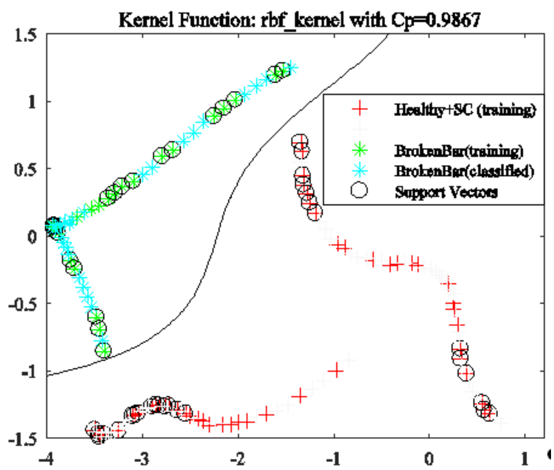

Fig.15. RBF for broken Bar (Cp=98.67%)

The following figures show the polynomial with different motor states:

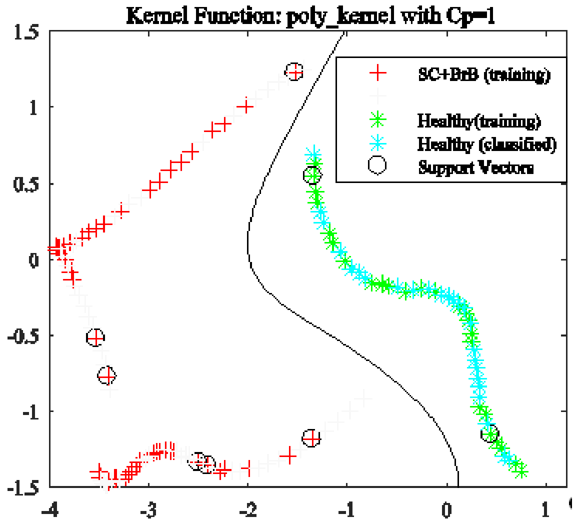

Fig.16. Polynomial n=2 for healthy motor (Cp=100%)

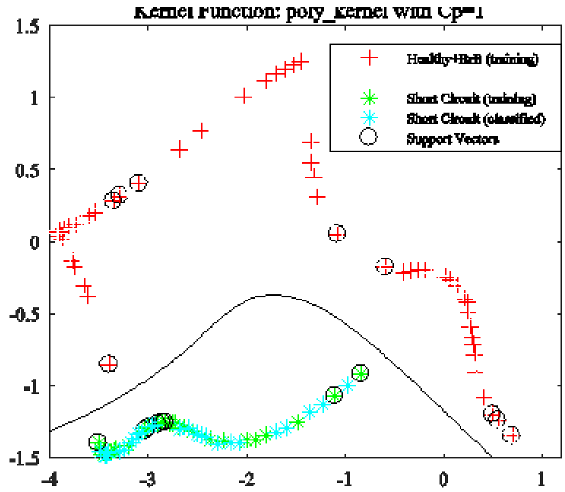

Fig.17. Polynomial n=2 for Short circuit (Cp=100%)

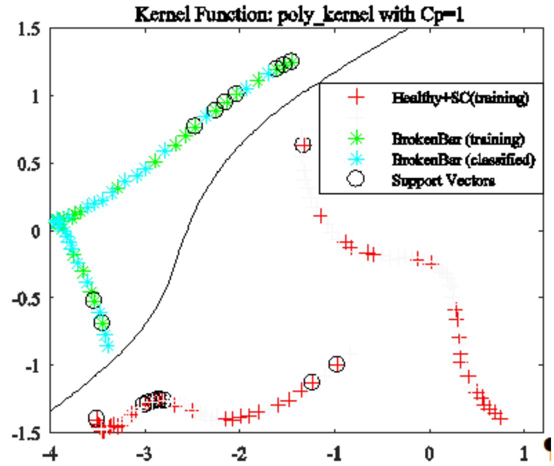

Fig.18. Polynomial n=2 for Broken Bar (Cp=100%)

The following figures show MLP results with different motor states:

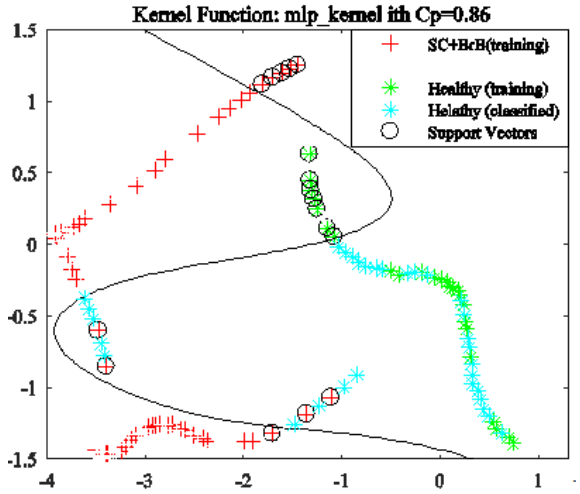


Fig.19. MLP [-1,1] for Healthy Motor (Cp=86%)

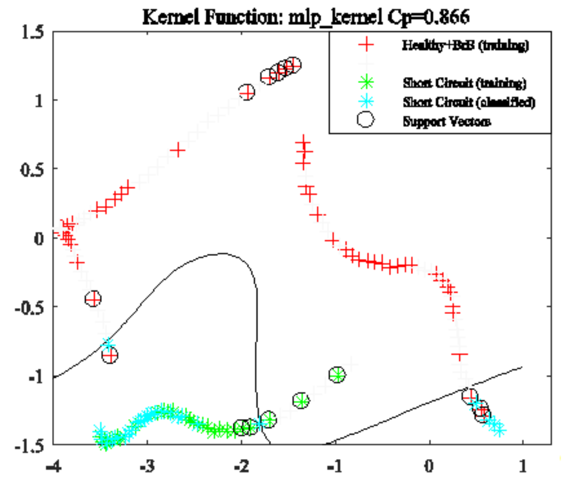


Fig.20. MLP [-1,1] for Short Circuit (Cp=86.6%)

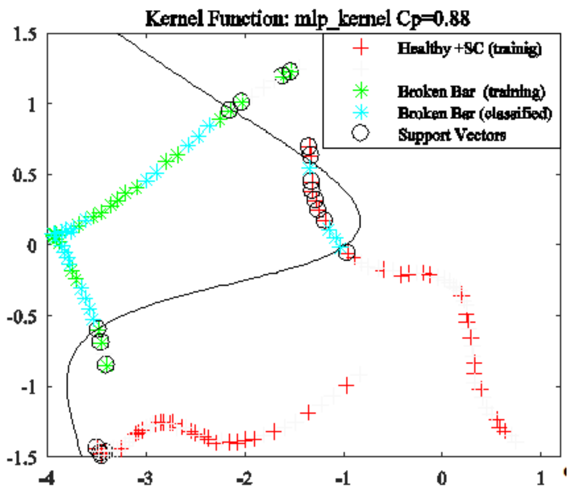


Fig.21. MLP [-1,1] for Broken bar (Cp=88%)

We note that use of KERNEL functions (polynomial Cp = 1 or RBF (Cp = 0.987) is more efficient compared to KERNEL MLP function (Cp = 0.866), hyperplane found between the two classes allowed perfect ranging of the desired state (high precision rate) regarding the induction motor operating conditions. We reached a table that includes the various behaviors state.

Table 1. Cp Performance class using KERNEL functions

| Sensor type B50/A | Class of performance Cp | | |
|---|---|---|---|
| | RBF | Polynomial n=2 | MPL [-1, 1] |
| Healthy | 0.987 | 1 | 0.86 |
| Short Circuit | 0.987 | 1 | 0.86 |
| Broken Bar | 0.987 | 1 | 0.88 |

## Use of SVM “One-vs.-All” strategy

The One-vs.-All strategy aims to create an SVM per class. All elements of each class are formed to create its class model. During test, each sample is tested regarding all other models to find the best class for which it is suitable. Usually, classification of an unknown sample is made on the basis of the maximum output among all SVMs [23-24].

After locating the fault and its nature (broken bar or short-circuit between turns or other); the second step is to evaluate this fault severity by comparing it to those of the same nature to quantify its severity order. This fault measurement must fulfil the same conditions as the other measurements, in particular regarding the load (same load).

In our case study, we considered two points: first, a short-circuit fault whose percentage is unknown, then it will be tested at standard (known) value classes (2%, 4%, 6%, 8% and 10% short circuits). Second, we consider a typical broken bar fault whose gravity order is not identified and which will be compared to the known classes (one broken bar or two broken bars).

The method presents excellent results for both applications; the faults level rank is established by the classifier irrespective of the proposed KERNEL function.

## Conclusion

Due to wide use of classification methods to detect anomalies in electrical machines and improve classification diagnosis performance, we have proposed a study based on the SVM classification method. As part of the monitoring of possible large faults, we tested several anomalies of different natures; not a single fault but simultaneous several faults were considered.

In this article, the diagnosis was approached by extracting the currents characteristics for same test conditions, including same load, using MCSA method as the first technique to establish a database to be introduced into the classification algorithms. . . The second technique via applying the SVM involves two steps; the first step was to identify the fault nature by separating it from the other characteristics of the induction motor via the use of the SVM (One-vs.-One), the other step leading to the evaluation of the fault severity level of same nature as this latter by using SVM (One-vs.-All). It has been shown from experimental results that the proposed methods provide an excellent classification accuracy of 100%.

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