Fault detection in induction motors based on artificial intelligence

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Abstract

Electric motors are essential components in most industrial processes. The various faults in induction machines can result in drastic consequences for an industrial process. The main problems are related to rising costs, worsening conditions in the process, and safety and quality of the final product. Many of these faults appear to be progressive. This work presents a contribution to the study of fault detection methods in electrical motors using Support Vector Machines (SVMs), trained by experimentally obtained vibration signals. The developed methodology is used to classify the excitation resulting from mechanical and electrical faults, in addition to normal operating condition. Through a selection of parameters, it is possible to reduce the number of entries able to represent the signals used for the SVMs training. The SVM procedure was compared with other two artificial intelligence techniques, the Fuzzy Logic (FL) and Artificial Neural Network (ANN). For the FL were created 43 rules and for ANN was evaluated three different architectures. Results showed that SVM has a good generalization, and requires less user knowledge for its application in comparison to FL and ANN.

1 Introduction

Electric motors are components present in many industrial processes, owing to their strength, mechanical simplicity, and adaptability to a variety of applications in the industry [1, 2, 3, 4].

With the high productivity levels at industrial plants, any unscheduled shutdown due to failure (unplanned corrective maintenance) can be very disruptive to the production process. In industries like nuclear power and petrochemical, techniques able to detect the fault's early onset could avoid more serious problems. In this sense, there are many studies focused on early fault detection. In this manner, over the past 30 years, several artificial intelligence techniques have been developed and applied in the monitoring processes of faults, among them, the Artificial Neural Networks (ANNs), Fuzzy Logic (FL) and Support Vector Machines (SVM) [5, 6, 7, 8].

Regarding the neural networks, it is important to note that the ANNs can be considered as “black boxes”; since they provide little explanation regarding the prediction and the fault detection processes [9]. Furthermore, the artificial neural networks are not portioned with training algorithms that maximize the generalization in a systematic manner, which can lead to overfitting the model over the data points [10].

Conversely, it is possible to implement early fault detection in fuzzy logic systems, and to interpret and analyze their results with a good theoretical basis. However, fuzzy logic presents some difficulties with its rule definitions, and its input data processing [9]. This feature requires an expert to create the respective rules.

Recently, support vector machines, are gaining more applications in the fault detection area because of its high success rate, and good generalization capability [11].

It is known that different methods for induction motor fault diagnosis were proposed, but in these studies, in general it is necessary different signals from different sensors to detect and differentiate mechanical and electrical faults. Kolla and Altman [6], train the ANN with voltage and current signals to detect faults in induction motors. Experimental tests achieved good results, but only electrical faults have been analyzed.

In other hand Baccarini et al. [1], used the SVM together with vibration signals to detect mechanical faults in induction motors. However, the electrical faults were not included, since this type of failure is typically detected using other sensor signals as current, voltage and flux.

In order to evaluate the research related to fault detection through support vector machines, Widodo and Yang [12] presented a survey of fault detection in machines using SVM; thus, concluding that support vector machines techniques are the most promising for fault diagnosis. They concluded also that more incentive and attention would be necessary as for the scarcity of works focused on the research for this concept's applications in the monitoring of the equipment's conditions and faults diagnosis.

Usually, Fuzzy Logic and ANN techniques, as SVM are trained using a database correlating measurement and corresponding fault. In practical application, the level of severity of faults may vary and not exactly match the database used for training. This can lead to false diagnosis.

This paper presents an artificial intelligence practical application for the detection, and diagnosis of mechanical and electrical faults in three phase induction motors. This study proposes a methodology to detect mechanical and electrical faults using only one accelerometer sensor for measuring vibration, under conditions of different levels of fault severity, by the use of a normalization process to improve the SVM accuracy rate.

2 Vibration Analysis and Fault Detection

Normally the vibration analysis is based on the assumption that faults can be detected by analyzing frequency characteristics. All faults cause a specific alteration of the frequency spectrum, compared to the normal operating condition.

Vibration analysis has been one of the most widely used techniques for fault detection and diagnosis, because of its potential, e.g., ease of use, relative low cost, non-intrusive technique, among others. The spectrum analysis of the vibration's signal can detect both mechanical and electrical failures.

However, analyzing the vibration in electric motors is not an easy task, since the vibration generated is the result of mechanical and magnetic forces interacting with its structure. Thus, the analysis of vibration is a problem that requires multidisciplinary knowledge, e.g., information about the dynamic signals of interest, modulation, conditioning, special tools for the diagnosis of faults and for the most important parameters choices.

There are various techniques to detect specific type of faults (e.g., analysis of current for electrical problems); however, the ability to detect a greater number of different faults with the same technique, would imply in costs reduction and process optimization.

For the detection of electrical faults with traditional techniques of predictive maintenance, it is necessary to remove the operation motor, for inter-turn short-circuit and broken bars testing. The phase unbalance detection requires access to power cables, which in the majority of cases are not easy available for measurements; consequently, a highly dangerous job for the operator.

Therefore, we use a single acceleration sensor for detecting mechanical and electrical faults. Following are some of the major mechanical faults: unbalance, misalignment, mechanical looseness, and among the electrical faults are inter-turn short circuit, phase unbalance, and broken bars.

2.1 Induction motor faults

The rotor unbalance is undoubtedly the major cause of vibrations in rotating machinery. This phenomenon is characterized by the presence of unbalanced mass in relation to the axes of rotation. The resulting vibration is predominantly radial, a strong component in the frequency of rotation ($1 \times f_r$) [13].

The misalignment is almost as common as the unbalance. The mechanical assemblies, usually has multiple shafts, bearings and couplings with different dynamic characteristics. In the misalignment, the vibration is greater in the radial direction, with strong components in harmonics from the frequency of rotation ($1 \times f_r$, $2 \times f_r$, $3 \times f_r$, $4 \times f_r$) [13].

The mechanical looseness is defined by the presence of multiple harmonics from the frequency of rotation ($1 \times f_r$), and it generates vibration in rotating machines due to loose screws, excessive clearances in the bearing, among others. The dominant plan is the radial with higher harmonics as well as sub harmonics of $1 \times f_r$ ($0.5 \times f_r$, $1.5 \times f_r$, $2.5 \times f_r$, etc..) [14].

The insulation fault is typically caused by contamination of the winding, abrasion, vibration or voltage surge. According to Nandi e Toliyat [15], the line's 19^{th} and 21^{st} harmonics (1260 Hz) are always present when there is a fault in the stator.

The phase unbalance or voltage unbalance is characterized by the existence of different voltage levels between two phases. [16], showed that in the vibration spectrum, the line's 2^{nd} harmonic (120 Hz) is related to the phase unbalance.

The break in the bars and the cold welds in the cage, are among the faults, frequent in the induction machines rotors. The characteristic symptoms are abnormal vibration and noise. Brito e Pederiva [17] demonstrated that in the spectrum of vibration, the detection of broken bars is made by taking into account $1 \times f_r \pm 2 \times s_f$, with s_f as the slip frequency of the electric motor.

3 Artificial Intelligence

3.1 Artificial Neural Network

The ANN tries to simulate the biological brain neural network in a mathematical model. It is a set simple processing unit, connected to each other, with weights assigned to the connections. According to a learning rule it is possible to modify these weights, so, the ANN can be trained to recognize a pattern given the training data. There are several transfer functions such as tanh, sigmoid, etc. There are several kinds of neural network structures proposed in the literature. The most used structure is the feed-forward network. There can be several hidden layers in the network. The Figure 1 shows two hidden layer. In this network, the number of input nodes and the number of output nodes are determined by the number of patterns to be identified. The number of nodes in the hidden layer is selected for an application, generally using a trial and error method. The neural network has to be trained so that it can identify the output patterns corresponding to the input pattern. There are several kinds of training algorithms suggested in the literature. The back-propagation is one of the most popularly used algorithms [6].

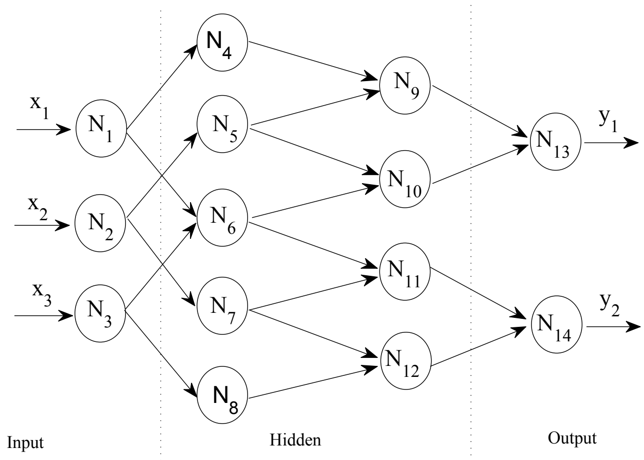


Figure 1: Feed-forward neural network.

3.2 Fuzzy Logic

The concept of fuzzy logic was introduced by Zadeh [18] to present vagueness in linguistic terms and express human knowledge in a natural way. With the FL is possible for control devices evaluate concepts unquantifiable, as thermal sensation (hot, warm, cold, etc.). In other hand, the FL is an extension of Boolean logic that admits intermediary values between, FALSE (0) and TRUE (1), e.g., MAYBE (0.5). That means, a fuzzy value is any value in a range between 0 and 1.

In practice, a fuzzy system can get certain knowledge, which allows it to make decisions with a high percent of accuracy. This knowledge expressed in rules and membership functions is obtained from the study, in this case, of the induction motor, through engineer experience. From the point of view that sees induction motor condition as a fuzzy concept, there has been some fuzzy logic approaches for diagnosis [8]. The lack of proper processing of fuzzy input data and the construction of the membership functions and rules, are presented as the major difficulties.

3.3 Support Vector Machine

Since the SVM constitutes of a technique grounded by the statistical learning theory, developed by Vapnik [19]. This theory establishes a series of principles to be followed in obtaining classifiers with good generalization, defined as its ability to correctly predict a class of new data from the same domain in which the learning occurred.

The task is to separate two classes by using a hyperplane induced from the training samples, producing a good performance classifier with the non-observed samples during training, i.e., with good ability of generalization.

The optimal separating hyperplane, created by the SVM must have maximum margin [20], and its margins define the points that will be called support vectors (SV). Figure 2, shows an example of a optimal separating hyperplane and two sets of data.

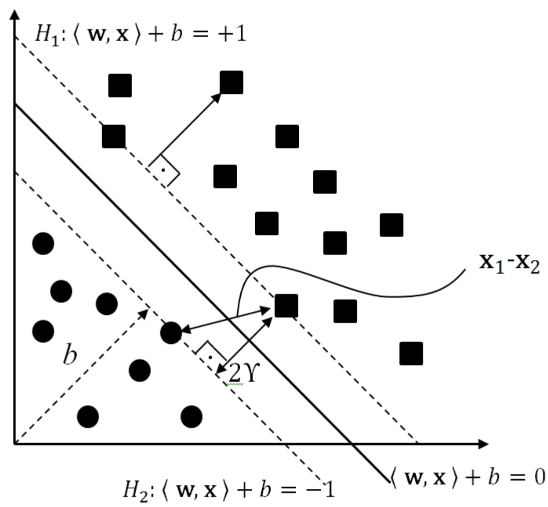


Figure 2: Optimal separating hyperplane.

The function that represents the hyperplane is linear. However, when the data are not linearly separable, the SVM map the input data in a space of higher dimension. When choosing a nonlinear mapping, a priori, the SVM constructs an optimal separation hyperplane in the characteristics space, and the functions transitioning from input to characteristics space are called kernel functions.

By introducing variables, the SVM widen the margin by relaxing its restrictions; thus, allowing for some misclassifications at the margin, yet, penalizing those errors through penalty parameter.

3.3.1 Multiple classes

The SVMs were originally formulated for the solution of binary classification problems; however, many classification problems have more than two classes.

The most direct way to generate multi-class classifiers from binary classification techniques is to decompose the multi-class problem into binary sub-problems. The outputs of binary predictors, generated in the solution of each of these sub-problems, are then combined to obtain the final classifier. The main decomposition methods are "One-Against-All", "One-Against-One", and "All-Against-All".

This article used the "one-against-one" method; even though, the "one-against-all" methodology is a good one with comparable performance; however, the "one-against-one" has a shorter training period [21, 22, 23]. The "one-against-one" method consists of the construction of a SVM for each pair of classes. Thus, for a problem with K classes, $k(k-1)/2$ SVMs are trained to differentiate the samples. Generally, the classification of an unknown pattern is made according to the maximum voting, where each SVM votes for a class.

4 Experimental set-up

The experimental set-up, Figure 3, was assembled at the Laboratory of Vibrations, School of Mechanical Engineering - University of Campinas.

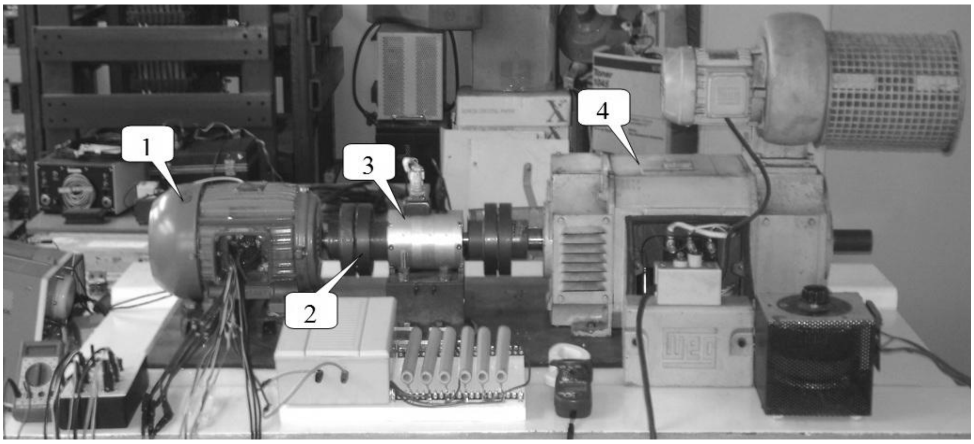


Figure 3: View of the experimental setup.

The faults were inserted in a three-phase motors {1}, squirrel cage rotor, 5 CV, 220V, 60Hz, category N, 44 bars, 36 slots, SKF 6205-2Z bearing, ID-1, frame 100L, class of insulation B.

A CC generator {4} feeding by the bank of resistance is used as a load system. Varying the excitement current of the CC generator field, it is obtained, consequently, the variation of the motor load. The generator is connected to the electric motor through flexible couplings {2}, and a torquimeter {3} that could guarantee the same operating condition in all the accomplished tests.

Six hundreds and eighty vibration signals were randomly collected, which are distributed among the six faults in the study. For the data collection, it employed the NI-6251 data acquisition device from National Instruments. This plate contains 16 analog input channels that can be sampled at up to 200 kHz and two digital counters of 24 bits each. The analog inputs have a resolution of 16 bits. The vibration signals were subjected to an anti-aliasing filter with a 2 kHz cutoff frequency. The implementation of the data acquisition algorithm used the MATLAB software.

The accelerometer was installed vertically on the electric motor coupled side. The signals were collected at a sampling frequency of 5 kHz and 20480 points, to cover the whole frequency band in which the defects, under study, are identified. It used a Hanning window and four averages were made in the signal from the frequency domain. The signals were transformed to the frequency domain using the FFT algorithm. Prior to testing, the bench was aligned, and balanced. Thus, it was possible to determine the motor-generator signature count, which were stipulated as maximum of 0.5 mm/s amplitude of vibration (measured in RMS) according to the VDI 2056 norm [24].

4.1 Faults Insertion

The unbalance was created by adding mass at different positions on a metal disk placed on the motor shaft. Misalignments were created by installing additional shims of specific thickness in the motor's base, to slightly lift it above the coupling axis. The mechanical looseness was created by loosening the screws at the base of the electric motor.

To simulate the low insulation among spirals from the same phase, four derivations were extracted in a coil. Those derivations were disposed externally, and linked in series (two each time) with a resistance bank, of 1Ω, 100W (each one) connected in parallel, and added to the circuit in order to control the current intensity of the inter-turn short circuit by approximately 10A, always staying the nominal load of the motor.

Each coil is constituted of 26 turns with the diameter wire equal to 16 AWG. As 6 coils form each phase; therefore, the total of turns for each phase equals to 156.

Consequently, the configuration allows the low insulation analysis (short circuit) between, at least, two turns and, at the maximum, 10 turns for the phase A, corresponding to the percentages of 1.2% (2/156) and 6.4% (10/156) of low insulation.

The unbalanced phase excitement was obtained by inserting a changeable resistance in series with the electric motor supplying one of the phases.

Lastly, the broken bars were simulated by drilling holes in the rotor bars, resulting in the breaking thereof.

4.2 Vibration signals selecting

This study uses the velocity values obtained from integration of accelerometer signal. From the velocity spectrum, the deterministic frequencies that most represent the faults was chosen (see section 2.1). It is necessary because data obtained from vibration spectrum analysis contain not only information about faults through the deterministic frequencies, but also some other that can be neglected, like noise. A total of 680 input patterns corresponding to different faults, as described in Table 1, were used.

Condition	**Number of patterns**
No Fault	170
Unbalance	110
Misalignment	110
Mech. looseness	110
Short circuit	60
Phase unbalance	60
Broken bars	60

Table 1: Number of training patterns per fault.

The input parameters were defined as: 1, 2, 3 and $4 \times f_r$ (f_r: frequency of rotation) for the detection of mechanical faults; 2, 19 and $21 \times f_l$ (f_l: line frequency) for inter-turn short-circuit and phase unbalance, and $1 \times f_r \pm 2 \times s_f$ for the broken bars.

Figure 4 shows the vibration amplitude values in $\mathbb{R}^3$ space for the selected input frequencies. It can be noticed that the sampled data are grouped and overlaid and thus, can not be linearly split.

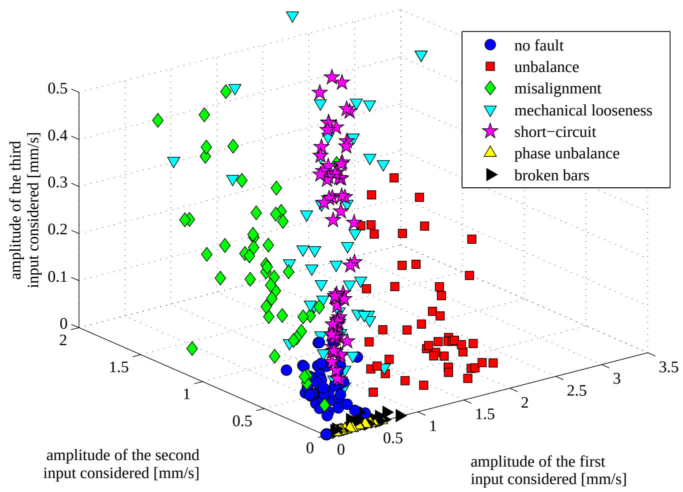


Figure 4: Pattern distribution for the data set.

4.3 Application of the SVMs

The RBF kernel (Radial Basis Function), conducted the SVM training. The RBF kernel was chosen because it maps the samples into a dimensional space superior than the initial problem, which allows it to work in non-linear situations, and it contains fewer hyperparameters that influence in the complexity of the model's choice [21].

The RBF kernel contains two hyperparameters, the C and the γ, for which the user must define the entry value. A wrong choice can lead to poor generalization of the classifier. To avoid this problem, the choices are made automatically. For automatization of the C and γ, choices, there is a v-fold cross validation that divides the training set in v subsets of equal size. Sequentially, a subset is tested using the trained classifier on the other $v-1$ subsets. Thus, each instance of the completely trained set is predicted with greater accuracy by the cross-validation. This step is important, since the cross-validation can prevent the overfitting [25].

Along with cross-validation, a grid-search is performed for the best values of C and γ. Several pairs of (C,γ) are judged and the one with the best cross-validation accuracy is chosen. To try an exponential growth of sequences C and γ is a practical method for the identification of the best parameters [25]. In the study, for both the faults, it sought between the values of $C = 2^{-5}, 2^{-4}, \ldots, 2^{15}$ and for $\gamma = 2^{-15}, 2^{-14}, \ldots, 2^{3}$.

4.4 Application of the ANN

In the use of ANNs some parameters are chosen by the user. One critical decision is to determine the appropriate architecture, that is, the number of layers, number of nodes in each layer [26].

Choose the best architecture by testing three different architectures topology. For the mechanical faults we use 4x3x1, 4x5x1 and 4x10x1 (which represent input x hidden x output), and for the electrical faults we use 3x3x1, 3x5x1 and 3x10x1. Topology that showed better results was 4x5x1 for mechanical faults and 3x3x1 for electrical faults [27].

The maximum error was kept below 0.5%, the learning rate, the momentum and the maximum number of epochs, are assumed as 0.01, 0.9 and 1000, respectively, and the weights was initialized randomly. In input and hidden layer neurons, we considered a sigmoidal activation function and output layer neurons use linear function. We use an activation velocity of 0.001.

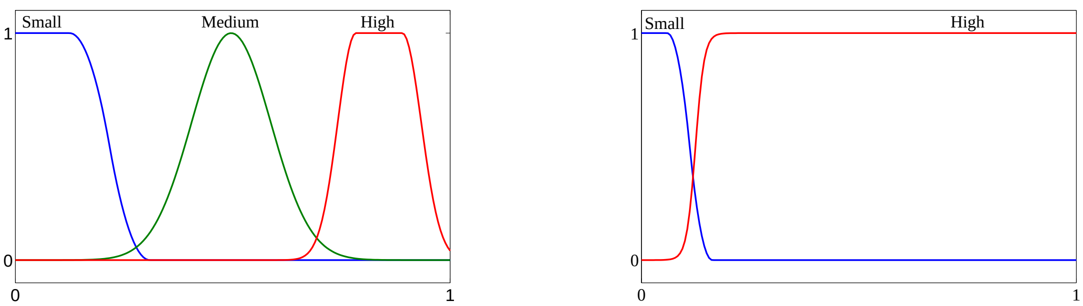
4.5 Application of the Fuzzy Logic

Different to SVM and ANN, for the fuzzy system we use as input variables: 1, 2 and $3 \times f_r$ to detect mechanical faults and for electrical faults we use as input variables: 2, 19 and $21 \times f_l$ (f_l: line frequency) for inter-turn short-circuit and phase unbalance, and $1 \times f_r \pm 2 \times s_f$ for the broken bars. The output variables represent the different kind of faults, Unbalance (UB), Misalignment (MA), Mechanical Looseness (ML), Short Circuit (SC), Phase Unbalance (PU) and Broken Bars (BB) and health condition (HC).

The amplitudes of the vibration signals (inputs) are categorised using three linguistic variables for mechanical faults $\{$Small (S), Medium (M) and High (H)$\}$ and two linguistic variables for electrical faults $\{$Small (S) and High (H)$\}$. The induction motor condition (outputs) are categorised as No Fault (NF), Intermediate Level (IL) and Critical Level (CL) for mechanical faults and categorised as No Fault (NF) and With Fault (WF) for electrical faults.

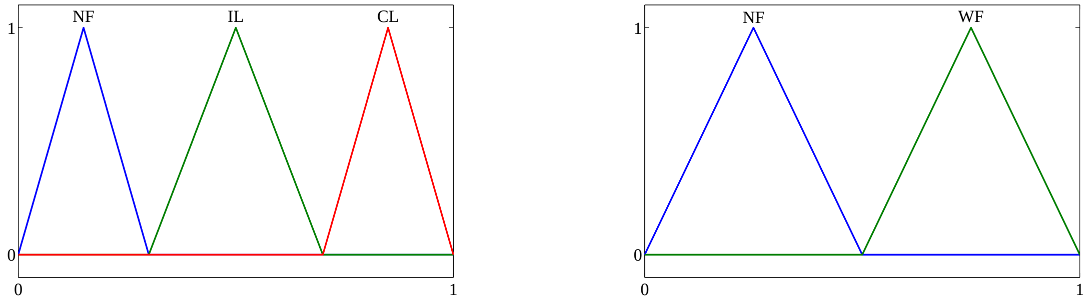
The system was tested with triangular, trapezoidal and Gaussian membership functions. It was found that the combination of Gaussian and triangular membership function is the most appropriated for fault diagnosis of induction motors using as input vibration signals [27].

Figure 5 shows an example of input membership functions for mechanical faults detection. Figure 6 shows the output membership functions for mechanical faults detection.



(a) Mechanical faults (b) Electrical faults

Figure 5: Membership functions for the normalized vibration signal.



(a) Mechanical faults (b) Electrical faults

Figure 6: Membership functions for the induction motor condition.

A fuzzy system can store certain knowledge, which allows it to make decisions with a high percent of accuracy. This knowledge is expressed in rules. Rules connect the inputs with the outputs to take the decision about the induction motors condition. Table 8 (mechanical faults) and Table 9 (electrical faults), (see section 7), shows the *if-then* rules. For example, interpreting Rule 1 from Table 8 we have: *if* $1 \times f_r$ is S and $2 \times f_r$ is S and $3 \times f_r$ is S *then* motor condition is NF for Unbalance, and NF for Misalignment end NF for Mechanical looseness, that means, the induction motor is health.

5 Faults diagnosis

For the input parameters, were chosen the amplitudes of the frequencies described above. The sets of mechanical and electrical faults were mixed together (mechanical with mechanical and electrical with electrical), and then partitioned in half. This process was conducted in triplicate; thus obtaining three subsets of training and three subsets of validation with varied data, and identified as set 1 (s1), set 2 (s2) and set 3 (s3).

The training and validation process used each of the different sets created. This subsets division with different data, aimed to verify the representativeness of the experimental data in relation to the faults inserted.

Table 2 and Table 3, shows the results of the Artificial Intelligence Techniques (AI) classification for both the mechanical and electrical faults, and the normal operating condition, respectively.

Fault	AI	s1 Hit Rate (%)	s2 Hit Rate (%)	s3 Hit Rate (%)
No Fault	SVM	96.00	96.00	98.00
	ANN	86.24	84.49	91.29
	FL	100	100	100
Unbalance	SVM	96.00	96.00	92.00
	ANN	90.80	86.97	83.35
	FL	96.00	96.00	88.00
Misalignment	SVM	88.00	88.00	88.00
	ANN	94.08	84.77	81.18
	FL	84.00	84.00	88.00
Mech. looseness	SVM	80.00	80.00	84.00
	ANN	74.65	70.72	60.43
	FL	72.00	84.00	80.00

Table 2: Percentage of correct detection for mechanical faults.

By the analysis of the results on Tables 2 and 3, it is possible to observe that all methodologies achieved satisfactory results. It is clear that there are differences in hit rate between the techniques. In general SVM achieved best results comparing with ANN and FL, when taking into account the SVM has less parameters that influence in percentage of correct detection, and it is easier to make a selection of these parameters automatically, avoiding erroneous choices, which would hinder the SVM performance. However, ANN has many

Fault	AI	s1 Hit Rate (%)	s2 Hit Rate (%)	s3 Hit Rate (%)
No Fault	SVM	100	100	100
	ANN	95.11	90.93	92.93
	FL	100	100	100
Short circuit	SVM	100	100	100
	ANN	91.22	89.73	83.61
	FL	100	100	100
Phase unbalance	SVM	77.78	100	100
	ANN	94.90	95.47	94.94
	FL	100	100	100
Broken bars	SVM	100	100	100
	ANN	92.60	93.23	91.48
	FL	88.89	83.33	77.78

Table 3: Percentage of correct detection for electrical faults.

parameters that can influence in percentage of correct detection, as architecture, and its automatic selection is an active research field.

FL is a technique that provides excellent results, but it should be noted the difficulty of creating rules and definition of the membership functions, which require much expert knowledge about the problem studied.

5.1 Fault levels

In practice, the machine may have different levels of vibration amplitude, which in turn can be classified in accordance with the norms. According to the VDI 2056 [24], machines with up to 20 HP power are considered without fail, when they have vibration levels up to 0.71 mm/s. They are regarded as level 1 (Permissible) when vibration levels are between 0.71 and 1.80 mm/s; level 2 (Tolerable) when vibration levels are between 1.8 and 4.50 mm/s, and level 3 (Impermissible) when the vibration levels are higher than 4.50 mm/s.

This study considers only two levels of severity: level 1 with vibration amplitudes between 0.71 and 1.80 mm/s, and level 2 with vibration amplitudes above 1.80 mm/s.

In electrical source failures, the vibration levels are relatively low; thus, the use of VDI 2056 is impossible. The levels were defined according to the intensity of the inserted faults. For the inter-turn short-circuit fault, when inserting two turns short circuited, it was considered as level 1, i.e., a very early stage of fault, and level 2 with ten turns short circuited. Ten is still a small number of turns short circuited, when compared with the motor's total number of turns; however, ten turns short circuited are more aggressive than two turns short circuited ones.

For the unbalance phase fault, level 1 was considered when the two phases voltage were at 220V and the third was at 210V and Level 2 when the two phases were at 220V and the third was at 200V. Lastly, level 1 had three broken bars and level 2 had seven broken bars.

5.2 Classification of faults at different levels of severity

So far, it was demonstrated the AI use for the classification of faults; however, during the training and verification phases, the severity levels of the input parameters fault remained the same (level 1). Nevertheless, in real situations, the equipment has different levels of faults. If the AI technique is trained with a level 1 of fault severity, it will not be able to correctly classify the same fault at level 2 of severity [27].

Thus, with the SVM and ANN model already trained to classify faults at level 1, it was decided to classify the level 2 with the same model. For this step, the user trains its SVM or ANN with the available data, and he will use it to classify the new data, except that this data is on another level. Table 4 and 5, shows the classification for different levels of severity for the mechanical and electrical faults, respectively. Regarding FL will be discussed later on.

Fault	AI	s1 Hit Rate (%)	s2 Hit Rate (%)	s3 Hit Rate (%)
Unbalance	SVM	44.00	80.00	48.00
	ANN	87.20	81.52	69.59
Misalignment	SVM	72.00	32.00	28.00
	ANN	49.91	56.94	43.49
Mech. looseness	SVM	60.00	16.00	74.00
	ANN	79.47	72.60	83.12

Table 4: Rating level 2 through the AI trained with the level 1 for mechanical faults.

Fault	AI	s1 Hit Rate (%)	s2 Hit Rate (%)	s3 Hit Rate (%)
Short circuit	SVM	66.67	77.78	88.89
	ANN	91.80	83.01	89.31
Phase unbalance	SVM	00.00	00.00	22.22
	ANN	97.48	95.26	97.66
Broken bars	SVM	00.00	11.11	44.44
	ANN	83.91	97.33	97.81

Table 5: Rating level 2 through the AI trained with the level 1 for electrical faults.

It can be observed by Tables 4 and 5 that when we have a trained SVM to faults at a level of severity 1 and ranks the same faults trained, but in another severity level the percentage of correct detection drop considerably for both mechanical and electrical faults. The same can be said for classification of mechanical faults using ANN, while for electrical faults the neural network was able to deal with this difference of levels.

When using faults on level 2 in fuzzy logic, the classification is not possible, therefore, membership functions were created according to the amplitudes of the fault level 1. So to deal with classification problem with more than one level of severity with fuzzy logic, must be recreated the membership functions.

5.3 Normalization

Due the low hit rates when training the SVM with a fault's level 1 and ranking other levels, we propose a normalization to deal with it.

The normalization consists of the following: for mechanical faults, normalize the amplitudes of harmonics of two, three, and four times the frequency rotation in relation to the amplitude of one time the frequency of rotation.

Regarding the electrical faults, for the inter-turn short-circuit fault, normalize the amplitudes of the harmonics two and nineteen times the frequency of line in relation to an amplitude of twenty-one times the frequency of line. For the unbalance phase fault, normalize the amplitudes of the harmonics of nineteen and twenty one times the frequency of line in relation to amplitude twice the frequency of line. Lastly, for the broken bars faults normalize the amplitudes of the sidebands of plus and minus two times the frequency of slip from the electric motor in relation to the amplitude of one time the frequency of rotation.

With this procedure, it is possible, e.g., to train the SVM with a fault at level 1 of severity and classify a fault on another level of severity, with better hit rates.

5.4 Ranking with the normalization

In this step, it was used a normalization proposal, to try to classify the fault at level 2 of severity, assuming that only level 1 data is available for training. The process consists of normalizing the input data at level 1, and then to train the SVM, followed by the normalization and ranking of the level 2 data.

Table 6, shows the SVM classification results for the mechanical faults with the normalization.

Fault	AI	s1 Hit Rate (%)	s2 Hit Rate (%)	s3 Hit Rate (%)
Unbalance	SVM	100	100	100
	ANN	77.53	85.40	85.60
Misalignment	SVM	100	100	100
	ANN	81.97	85.32	72.40
Mech. looseness	SVM	72.00	76.00	92.00
	ANN	47.97	73.13	33.62

Table 6: Ranking level 2 of severity with a SVM trained with the level 1 for mechanical faults with the normalization.

Table 7, shows the SVM classification results for the electrical faults with the normalization.

Fault	AI	s1 Hit Rate (%)	s2 Hit Rate (%)	s3 Hit Rate (%)
Short circuit	SVM	100	100	100
	ANN	91.92	98.83	99.85
Phase unbalance	SVM	88.89	88.89	100
	ANN	90.72	98.08	89.26
Broken bars	SVM	100	100	100
	ANN	90.59	99.63	99.83

Table 7: Ranking level 2 of severity with a SVM trained with the level 1 for electrical faults with the normalization.

Regarding SVMs, normalization could deal with the problem of classification of other severity levels improving hit rates for both mechanical failures and for electrical faults. ANNs were not influenced as much as the SVM due to the different levels for training and classification. However, with the normalization was possible to achieve better hit rates, but lower than those obtained with the SVM with normalized data.

Importantly, better results can be obtained by modifying the various parameters of the ANNs. However, obtaining these best parameters is not as trivial as for SVMs. This choice of parameters to train the ANN is an active research field.

6 Conclusion

This paper discussed the use of SVM, ANN and FL to detect and diagnose faults in induction motors from mechanical failures (unbalance, misalignment and mechanical looseness) and electrical (inter-turn short circuit, phase unbalance and broken bars) beyond the normal operating condition. It was observed through the vibration spectra, that all tests demonstrated a good repeatability and without interference problems, ensuring a reliable analysis of the results.

SVM showed a technique with very good results. In comparison with the ANN, the SVM is not dependent on many parameters which influence the percentage of correct detections. On the other hand, although the LF is a technique that produces excellent results, its use is strongly dependent on an expert who knows the process to be analyzed.

The presented methodology allows the use of SVMs in practical applications, as a form of online monitoring by an operator not very knowledgeable in analysis and fault detection. According to the adopted procedures, the trained SVM was able to characterize both mechanical and electrical faults using only one sensor. The proposed normalization proved efficient in the process of identifying faults of different severity levels, improving the hit rates in relation to the standard training.

Also noteworthy is that the development of experimental techniques of SVM, combined with traditional predictive maintenance techniques allows automatization of the detection, and diagnosis of equipment's faults.

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References

[1] L. M. R. Baccarini, V. V. R. Silva, B. R. Menezes, and M. C. Walmir. SVM practical industrial application for mechanical faults diagnostic. *Expert Systems with Applications*, 38(6):6980 – 6984, 2011.

[2] A. Widodo, B. Yang, and T. Han. Combination of independent component analysis and support vector machines for intelligent faults diagnosis of induction motors. *Expert Systems with Applications*, 32(2):299 – 312, 2007.

[3] V. Sugumaran, G.R. Sabareesh, and K.I. Ramachandran. Fault diagnostics of roller bearing using kernel based neighborhood score multi-class support vector machine. *Expert Systems with Applications*, 34(4):3090 – 3098, 2008.

[4] D. G. Ece and M. Basaran. Condition monitoring of speed controlled induction motors using wavelet packets and discriminant analysis. *Expert Systems with Applications*, 38(7):8079 – 8086, 2011.

[5] S. R. Kolla and L. Varatharasa. Identifying three-phase induction motor faults using artificial neural networks. *ISA Transactions*, 39(4):433 – 439, 2000.

[6] S. R. Kolla and S. D. Altman. Artificial neural network based fault identification scheme implementation for a three-phase induction motor. {*ISA*} *Transactions*, 46(2):261 – 266, 2007.

[7] C. T. Kowalski and T. Orlowska-Kowalska. Neural networks application for induction motor faults diagnosis. *Mathematics and Computers in Simulation*, 63(3-5):435 – 448, 2003.

[8] P. V. J. Rodríguez and A. Arkkio. Detection of stator winding fault in induction motor using fuzzy logic. *Applied Soft Computing*, 8(2):1112 – 1120, 2008.

[9] V. N. Ghate and S. V. Dudul. Induction machine fault detection using support vector machine based classifier. *WTOS*, 8:591–603, May 2009.

[10] K. Hornik, M. Stinchcombe, and H. White. Multilayer feedforward networks are universal approximators. *Neural Netw.*, 2:359–366, July 1989.

[11] B. Samanta, K.R. Al-Balushi, and S.A. Al-Araimi. Artificial neural networks and support vector machines with genetic algorithm for bearing fault detection. *Engineering Applications of Artificial Intelligence*, 16(7-8):657 – 665, 2003.

[12] A. Widodo and B. Yang. Support vector machine in machine condition monitoring and fault diagnosis. *Mechanical Systems and Signal Processing*, 21(6):2560 – 2574, 2007.

[13] P. Girdhar and C. Scheffer. *Practical machinery vibration analysis and predictive maintenance*. Elsevier, 2004.

[14] R. Mobley and R. K. Keith. *Vibration Fundamentals*. Butterworth-Heinemann, 1999.

[15] S. Nandi and H.A. Toliyat. Novel frequency domain based technique to detect incipient stator inter-turn faults in induction machines. In *Industry Applications Conference, 2000. Conference Record of the 2000 IEEE*, volume 1, pages 367–374, 2000.

[16] P. C. M. Lamim Filho, R. Pederiva, and J. N. Brito. Detection of stator winding faults in induction machines using an internal flux sensor. In *Diagnostics for Electric Machines, Power Electronics and Drives, 2007. SDEMPED 2007. IEEE International Symposium on*, pages 432 –437, sept. 2007.

[17] J. N. Brito and R. Pederiva. Using artificial intelligence tools to detect problems in induction motors. In *Proceedings of the 1st International Conference on Soft Computing and Intelligent Systems (International Session of 8th SOFT Fuzzy Systems Symposium) and 3rd International Symposium on Advanced Intelligent Systems (SCIS & ISIS 2002), Suzuka, Japão*, volume 1, 2002.

[18] L. A. Zadeh. Fuzzy sets. *Information and Control*, 8:338–353, 1965.

[19] V. N. Vapnik. *The nature of statistical learning theory*. Springer-Verlag New York, Inc., New York, NY, USA, 1995.

[20] B. Scholkopf and A. J. Smola. *Learning with kernels: Support vector machines, regularization, optimization, and beyond*. The MIT Press, Cambridge, Massachusetts, London, England, 2002.

[21] C. W. Hsu and C. J. Lin. A comparison of methods for multiclass support vector machines. *IEEE Transactions on Neural Networks*, 13(2002):415–425, 2002.

[22] A. Widodo and B. Yang. Application of nonlinear feature extraction and support vector machines for fault diagnosis of induction motors. *Expert Syst. Appl.*, 33:241–250, July 2007.

[23] T.-Y. Wang and H.-M. Chiang. One-against-one fuzzy support vector machine classifier: An approach to text categorization. *Expert Systems with Applications*, 36(6):10030 – 10034, 2009.

[24] VDI. VDI 2056: Criteria for assessing mechanical vibrations of machines, 1964.

[25] C. W. Hsu, C. C. Chang, and C. J. Lin. *A practical guide to support vector classification*. Department of Computer Science and Information Engineering, National Taiwan University, Taipei, Taiwan, 2003.

[26] J. M. Zurada. *Introduction of artificial neural systems*. St. Paul: West Publishing, 1992.

[27] V. A. D. Silva. Fault detection in induction motors using support vector machines. Master's thesis, Faculdade de Engenharia Mecânica, Universidade Estadual de Campinas, Campinas, Fev 2012.

7 Appendix

7.1 Rules for Fuzzy Logic

Rules	Inputs			Outputs		
	1xf_r	2xf_r	3xf_r	Unbalance	Misalignment	Mechanical Looseness
01	S	S	S	NF	NF	NF
02	S	S	M	NF	NF	NF
03	S	S	A	NF	CL	NF
04	S	M	S	NF	IL	NF
05	S	M	M	NF	IL	NF
06	S	M	A	NF	CL	NF
07	S	A	S	NF	CL	NF
08	S	A	M	NF	CL	NF
09	S	A	A	NF	CL	NF
10	M	S	S	IL	NF	NF
11	M	S	M	IL	IL	NF
12	M	S	A	IL	CL	NF
13	M	M	S	NF	NF	CL
14	M	M	M	NF	NF	CL
15	M	M	A	NF	CL	CL
16	M	A	S	NF	CL	NF
17	M	A	M	NF	CL	NF
18	M	A	A	NF	CL	NF
19	A	S	S	CL	NF	NF
20	A	S	M	CL	IL	NF
21	A	S	A	CL	CL	NF
22	A	M	S	CL	IL	NF
23	A	M	M	CL	IL	IL
24	A	M	A	CL	CL	NF
25	A	A	S	CL	CL	NF
26	H	H	M	CL	CL	IL
27	H	H	H	CL	CL	CL

NF - No Fault IL - Intermediate Level CL - Critical Level

Table 8: Rules for mechanical faults.

Rules	Inputs						Outputs		
	$2\text{x}f_l$	$19\text{x}f_l$	$21\text{x}f_l$	$1\text{x}f_r - 2\text{x}s_f$	$1\text{x}f_r$	$1\text{x}f_r + 2\text{x}s_f$	Short Circuit	Phase Unbal-ance	Broken Bars
01	S	S	S	-	-	-	NF	NF	-
02	S	S	H	-	-	-	WF	NF	-
03	S	H	S	-	-	-	NF	NF	-
04	S	H	H	-	-	-	WF	NF	-
05	H	S	S	-	-	-	NF	WF	-
06	H	S	H	-	-	-	WF	WF	-
07	H	H	S	-	-	-	NF	WF	-
08	H	H	H	-	-	-	WF	WF	-
09	-	-	-	S	S	S	-	-	NF
10	-	-	-	S	S	H	-	-	NF
11	-	-	-	S	H	S	-	-	NF
12	-	-	-	S	H	H	-	-	WF
13	-	-	-	H	S	S	-	-	NF
14	-	-	-	H	S	H	-	-	NF
15	-	-	-	H	H	S	-	-	WF
16	-	-	-	H	H	H	-	-	WF

NF - No Fault   WF - With Fault

Table 9: Rules for electrical faults.