



LEAST SQUARE SUPPORT VECTORS MACHINES APPROACH TO DIAGNOSIS OF STATOR WINDING SHORT CIRCUIT FAULT IN INDUCTION MOTOR

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Abstract

Various approaches have been proposed to monitor the state of machines by intelligent techniques such as the neural network, fuzzy logic, neuro-fuzzy, pattern recognition. However, the use of LS-SVM. This article presents an automatic computerized system for the diagnosis and the monitoring of faults between turns of the stator in IM applying the LS-SVM least square support vector machine. In this study for the detection of short circuit faults in the stator winding of the induction motor. Since it requires a mathematical model suitable for modelling defects, a defective IM model is presented. The proposed method uses the stator current as input and at the output decides the state of the motor, indicating the severity of the short-circuit fault.

Keywords: (Induction Motor, Inter-turn short circuit, Fault diagnosis, least square support vector machine (LS-SVM)).

1. INTRODUCTION

Although the asynchronous machine is robust, it can present, like any other electrical machine, electrical or mechanical breakdowns due to heavy duty cycles, poor working environment, installation and manufacturing factors, etc. Thus, because of the important and costly consequences that the appearance of a defect can have on industrial processes, the diagnosis of faults has been the subject of growing interest for two decades.

One of the most common faults is stator winding shorted turns, which covers approximately 30%-40% of the overall fault conditions in IMs [1]. Therefore, fast detection techniques able to detect these kinds of faults at an early stage of evolution are particularly welcome, in order to avoid the catastrophic failure in industrial process [2].

Several techniques have been studied during the last two decades, related to the analysis of the presence of internal faults in the stator windings of induction motors. There are references to some of these techniques in [1], [3], [4].

Three main solution techniques are commonly used in the literature in order to detect shorted turns in stator windings. The first technique is based on signal analysis, which often uses spectral tools to underline specific frequency components related to the fault [5], [6]. The second technique is related to knowledge-based approach [5], [7], [8]. The third class is based on state or parameters

estimation and implies the use of mathematical models of the studied system [9], [10], [11], [12].

There has been increasing efforts dedicated in establishing AI based models to predict real-world time-dependent data. such as the Artificial Neural Network (ANN), Adaptive Network based Fuzzy Inference System (ANFIS), Support Vector Machine (SVM), and Least Squares Support Vector Machine (LS-SVM). Support vector machines have been utilized as a popular algorithm realized from the machine learning [13]. The basic idea of Support Vector Machines (SVM) is to find a hyper-plane in an N-dimensional space (N number of features) that differentiates classifies the data points. In order to convert not separable problem to separable problem, SVM used functions called kernels which transform low dimensional data space to a higher dimensional space features. LS-SVM is a modification of the original SVM where the resulting optimization problem has half the number of parameters and the model is optimized by solving a linear system of equations instead of a quadratic programming [13-14].

In this paper, LS-SVM technique is proposed for fault diagnosis and classification of the short-circuit in the stator phases of an induction machine using information provided by the stator current signature. This monitoring system will provide information on the operation of the machine to the operators who operate it. It is also able to cause in severe cases a shutdown of the machine or to allow the production system to continue to operate in degraded mode in case of problems do not require

an immediate shutdown. The rest of this paper is structured as follows. Sections 2, 3 and 4 give a short presentation of different types of stator winding faults, modelling of a squirrel-cage induction motor with inter-turn short circuit in stator phase. Section 5 describes the *LS-SVM* approach followed by the proposed methodology in section 6. Section 7 is devoted to simulation results and conclusion of this study is conducted in the last section.

2. STATOR FAULTS

In order to take into account the presence of windings of inter-turn short-circuits in the stator of an IM, an original model has been proposed in reference [11]. Figure 1 shows the defective model of the stator in the Park axes with an overall leak reported to the stator. The short-circuit current (i_{dqcc}) is represented by the equivalent fault impedance $[Z_{cc}]$ which deflects part of the stator current. By extending this model to each phase, three short-circuit impedances ($[Z_{cc1}]$, $[Z_{cc2}]$ and $[Z_{cc3}]$ for phases a_1 , b_2 and c_2 , respectively) are added to the healthy part of the *IM* model

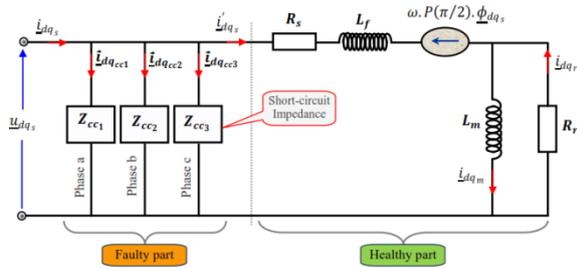


Fig. 1. Stator faulty model of induction machine

The stator fault model that we have just presented offers the advantage of explaining the fault through a resistive quadrupole dedicated to the faulty winding. The short-circuit quadrupole then responsible for explaining the fault through the two parameters θ_{cc} and μ_{cc}

1. The localization parameter θ_{cc} : This parameter can take only the three values: 0 , $2\pi/3$ and $4\pi/3$ corresponding to the short-circuit on the phase a_s , b_s , or c_s , respectively,
2. The detection parameter μ_{cc} : is equal to the ratio between the number of inter-turn short-circuits windings (n_{cck}) and the whole number of turns in the healthy phase (n_s). This parameter, which allows us to quantify the unbalance, is given by:

$$\mu_{cck} (\%) = (n_{cck} / n_s) \cdot 100$$

4. MODELLING OF THE ASYNCHRONOUS MACHINE "IN THE PRESENCE OF THE FAULTY"

For the simulation, the model in the representation of the fourth order state space of the *IM* with a winding fault is given by:

$$\begin{cases} \dot{x} = f(x) + g \cdot u \\ y = h(x) + H(x) \cdot u \end{cases} \quad (1)$$

With

$x = [i_{ds}' \ i_{qs}' \ \phi_{dr} \ \phi_{qr} \ \omega \ \theta]^T$: stat vector
 $u = [u_{ds} \ u_{qs} \ C_r]^T$ and $y = [i_{ds} \ i_{qs} \ \omega]^T$: machine inputs and outputs

$$f(x) = \begin{bmatrix} -\frac{R_s + R_r}{L_f} \cdot i_{ds}' + \omega \cdot i_{qs}' + \frac{R_r}{L_m L_f} \cdot \phi_{dr} + \frac{\omega}{L_f} \cdot \phi_{qr} \\ -\omega \cdot i_{ds}' - \frac{R_s + R_r}{L_f} \cdot i_{qs}' - \frac{\omega}{L_f} \cdot \phi_{dr} + \frac{R_r}{L_m L_f} \cdot \phi_{qr} \\ R_r \cdot i_{ds}' - \frac{R_r}{L_m} \cdot \phi_{dr} \\ R_r \cdot i_{qs}' - \frac{R_r}{L_m} \cdot \phi_{qr} \\ \frac{p^2}{J} \cdot (i_{qs}' \cdot \phi_{dr} - i_{ds}' \cdot \phi_{qr}) - \frac{f_2}{J} \cdot \omega \end{bmatrix} \quad (2)$$

$$g = \begin{bmatrix} \frac{1}{L_f} & 0 & 0 \\ 0 & \frac{1}{L_f} & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & -\frac{p}{J} \\ 0 & 0 & 0 \end{bmatrix} \quad (3)$$

$$h(x) = \begin{bmatrix} i_{ds}' \\ i_{qs}' \\ \omega \end{bmatrix} \quad (4)$$

$$H(x) = \begin{bmatrix} \frac{2}{3 \cdot R_s} \cdot \sum_{k=1}^3 \mu_{cck} \cdot p(-\theta) \cdot Q(\theta_{cck}) \cdot p(-\theta) & 0 \\ 0 & 0 \end{bmatrix} \quad (5)$$

5. LEAST SQUARES SUPPORT VECTOR MACHINES

LS-SVM is based on concepts of machinery learning. For that we establish the model on two steps:

- training
- test

In the first step, we consider a given training set [15-20] as follows:

$$\{x_i, y_i\} \phi \in \mathfrak{R}^2, i=1, 2, \dots, N$$

With x_i input data, and y_i input data. Regression model is based non-linear mapping function ϕ

$$y = w^T \phi(x) + b \quad (6)$$

Where w is the weight vector and b is the bias term. As in *SVM*, it is necessary to minimize a cost function C containing a penalized regression error, as follows [17-20]:

$$\min C(w, e) = \frac{1}{2} w^T w + \frac{1}{2} \gamma \sum_{i=1}^N e_i^2 \quad (7)$$

Subject to equality constraints:

$$y = w^T \phi(x_i) + b + e_i, i=1, 2, \dots, N \quad (8)$$

Solving this optimization problem, require Lagrange function (9). α_i are Lagrange multipliers

$$L(w, b, e, \alpha) = \frac{1}{2} \|w\|^2 + \gamma \sum_{i=1}^N e_i^2 - \sum_{i=1}^N \alpha_i \{w^T \phi(x_i) + b + e_i - y_i\} \quad (9)$$

We need to search solutions of partial derivatives with respect to w , b , e_i and α_i which give [17-20]:

$$w = \sum_{i=1}^N \alpha_i \phi(x_i) = \sum_{i=1}^N \gamma e_i \phi(x_i) \quad (10)$$

Where a positive definite Kernel is used as follows:

$$K(x_i, x_j) = \phi(x_i)^T \phi(x_j) \quad (11)$$

Putting the result of (10) into (6), the following result is obtained:

$$y = \sum_{i=1}^N \alpha_i \phi(x_i)^T \phi(x) + b \quad (12)$$

For a point y_i to be evaluated it is:

$$y_i = \sum_{i=1}^N \alpha_i \phi(x_i)^T \phi(x_j) + b \quad (13)$$

In addition to solve nonlinear regression it is enough to change the inner product of $\langle \Phi(x_i), \Phi(y_i) \rangle$ (12) by a kernel function and the ij th element of matrix K equals to (11)

This means as result a nonlinear regression function:

$$y = \sum_{i=1}^N \alpha_i K(x_i, x) + b \quad (14)$$

For a point x_j to be evaluated it is:

$$y_j = \sum_i \alpha_i K(x_i, x_j) + b \quad (15)$$

For LS-SVM, there are many kernel functions (linear, polynomial, radial basis function (RBF), spline, bspline, sigmoid, etc. However, the more used kernel function is RBF, a simple Gaussian function. It is defined by (16). σ_{sv}^2 is the squared variance of the Gaussian function. It should be optimized by the user, to obtain the support vector. α of the RBF kernel should be stressed and it is very important to make a careful model selection of the tuning parameters, in combination with the regularization constant γ , in order to achieve a good generalized model.

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{\sigma_{sv}^2}\right) \quad (16)$$

6. METHODOLOGY

This section discusses the proposed methodology which includes feature extraction; Database selection and the proposed LS-SVM for stator winding short-circuit fault diagnosis.

6.1. Feature extraction

The proposed LS-SVM approach is trained and tested to identify the stator winding inter-turn short circuit fault. It evaluates the input stator current of the same phase and decides the motor condition as output by indicating the percentage of inter-turn short circuit fault occurred in the motor (Figure 2).

The input variable ($Max(i_{sa})$) of the LS-SVM algorithm represents the values of the maximum amplitude of the stator current $i_{sa}(t)$ in different working conditions of the motor. The output variable takes five values describing the indication of the short-circuits fault:

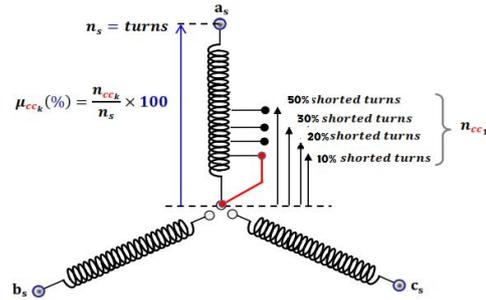


Fig. 2. Stator winding configuration with shorted turns faults

- 0: Healthy motor.
- 1: 10% shorted turns.
- 2: 20% shorted turns.
- 3: 30% shorted turns.
- 5: 50% shorted turns.

6.2. Database selection

A database constituted by inputs and output data sets has been applied to train and test the LS-SVM approach, the inputs-outputs data are collected through simulations in *Matlab* environment. The data set utilized derived from simulation are composed of 60 samples. The training set is composed of 30 samples representing the maximum amplitude of the stator current i_{saMax} under different load conditions $T_L=0, 1, 2, 3, 4$ and $5 Nm$.

The test set is composed of 30 samples representing the maximum amplitude of the stator current i_{saMax} under different load conditions $T_L=0.5, 1.5, 2.5, 3.5, 4.5$ and $5.5 Nm$ are used to test its performance. Each pattern of the training and testing set comprises one input stator current signature i_{saMax} and one output which represent the indication of severity of the short-circuits fault (*Indic*). Figure 3 summarize the process that LS-SVM used for stator winding short-circuit fault diagnosis.

It is noted that, the induction machine is simulated in open-loop and the LS-SVM detection method is used to evaluate the input stator current (i_{as}) and decides the motor condition as output by indicating the severity of the short-circuits fault.

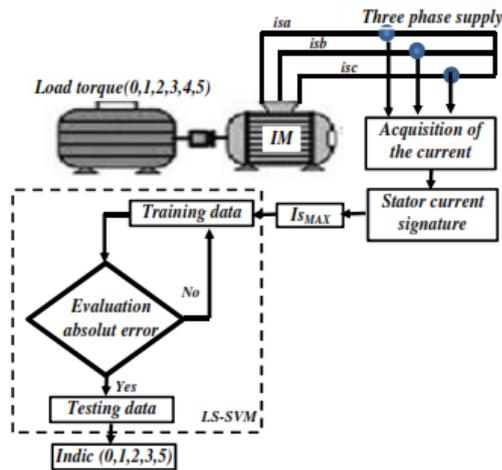


Fig. 3. Block diagram of *LS-SVM* for stator winding short-circuit fault diagnosis

Table 1. Database for training and testing

cc %	Training set		Testing set		
	T_L	Input $Max(i_{as})$	T_L	Input $Max(i_{as})$	Indication (indic)
0%	0	3,5574	0.5	3,5602	<u>0</u>
0%	1	3,5775	1.5	3,6086	<u>0</u>
0%	2	3,6537	2.5	3,7123	<u>0</u>
0%	3	3,7841	3.5	3,8684	<u>0</u>
0%	4	3,9647	4.5	4,0722	<u>0</u>
0%	5	4,1903	5.5	4,3184	<u>0</u>
10%	0	9,5708	0.5	9,7547	<u>1</u>
10%	1	9,9494	1.5	10,1347	<u>1</u>
10%	2	10,3357	2.5	10,5335	<u>1</u>
10%	3	10,7400	3.5	10,9522	<u>1</u>
10%	4	11,1699	4.5	11,3933	<u>1</u>
10%	5	11,6228	5.5	11,8587	<u>1</u>
20%	0	18,0303	0.5	18,2184	<u>2</u>
20%	1	18,4315	1.5	18,6132	<u>2</u>
20%	2	18,8375	2.5	19,0337	<u>2</u>
20%	3	19,2530	3.5	19,4834	<u>2</u>
20%	4	19,7235	4.5	19,9746	<u>2</u>
20%	5	20,2383	5.5	20,5166	<u>2</u>
30%	0	26,7037	0.5	26,8866	<u>3</u>
30%	1	27,1105	1.5	27,2743	<u>3</u>
30%	2	27,5216	2.5	27,6961	<u>3</u>
30%	3	27,9371	3.5	28,1595	<u>3</u>
30%	4	28,4147	4.5	28,6888	<u>3</u>
30%	5	28,9864	5.5	29,3148	<u>3</u>
50%	0	44,1895	0.5	44,3518	<u>5</u>
50%	1	44,6003	1.5	44,709	<u>5</u>
50%	2	45,0148	2.5	45,1097	<u>5</u>
50%	3	45,4332	3.5	45,5751	<u>5</u>

50%	4	45,8556	4.5	46,1498	<u>5</u>
50%	5	46,5135	5.5	46,9782	<u>5</u>

6.3. Fault detection of stator using *LS-SVM*

As mentioned above, the database of learning inputs / outputs which based on the simulation results derived from the motor behaviour without and with faults is used to train the proposed approach and to test its performance.

Once the data is grouped, we present them as input to the *LS-SVM* approach, the system performs its learning so that it can be ready to predict the severity of the short-circuit fault. We perform a test to validate the performance of the system by presenting as input the new data that are not part of the learning base. Once the test has been successfully completed (acceptable prediction error), the system is ready to classifier the severity of the short-circuit fault. In this paper, the parameters of *LS-SVM* approach have been selected after several tests. Therefore, the parameters adopted for this study are: $\gamma=1000$, $\sigma^2=0.01$.

7. RESULTS AND DISCUSSION

7.1. Healthy motor operation:

The simulation of the model of the healthy machine made it possible to draw the curves of the electromechanical quantities (stator current, torque and speed) with an introduction of a resistant pair of $T_r = 3 \text{ Nm}$ at the moment 0.7 s

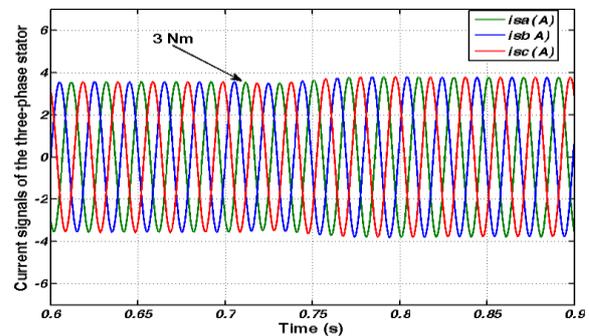


Fig. 4. Stator current of the healthy motor under load ($T_L = 3 \text{ Nm}$ at $t=0.7 \text{ s}$)

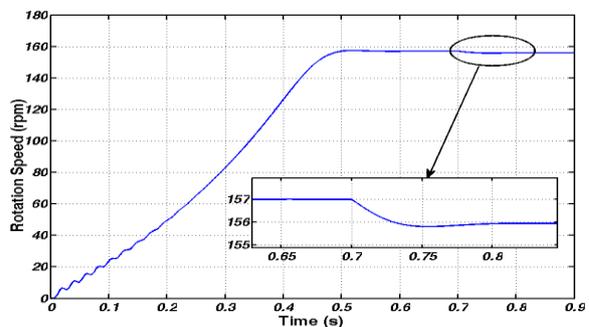


Fig. 5. Speed of rotation of the healthy motor under load ($T_L = 3 \text{ Nm}$ at $t=0.7 \text{ s}$)

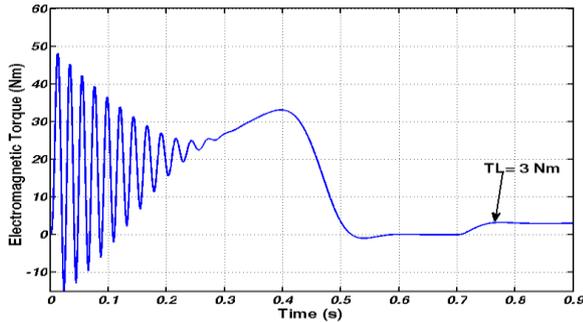


Fig. 6. Electromagnetic torque of the healthy motor under load ($T_L = 3 \text{ Nm}$ at $t=0.7\text{s}$)

7.2. Operation with short circuit fault 20%

We will now present the simulation results for an operation of the *IM* with short-circuit fault between stator turns, the degree of the short circuit is 20% at the instant of 0.9s.

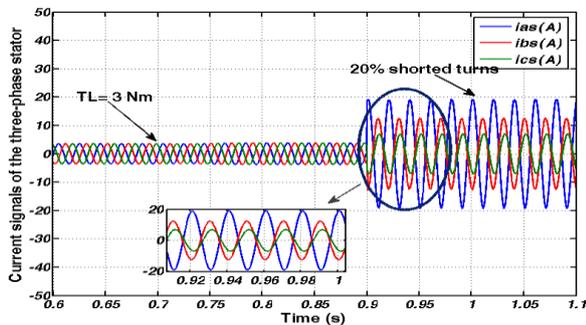


Fig. 7. Stator current motor with short circuit (20% at $t=0.9\text{s}$) under load ($T_L = 3 \text{ Nm}$ at $t=0.7\text{s}$)

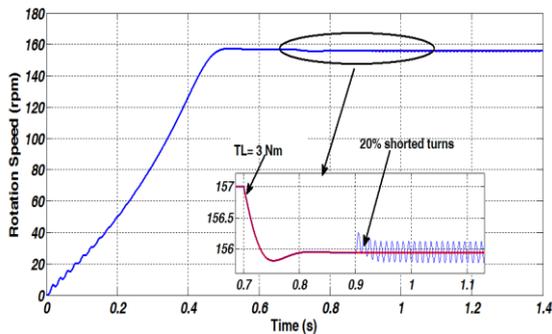


Fig. 8. Speed of rotation with short circuit (20% at $t=0.9\text{s}$) under load ($T_L = 3 \text{ Nm}$ at $t=0.7\text{s}$)

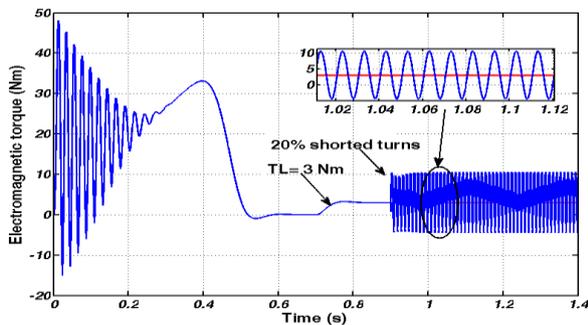


Fig. 9. Electromagnetic torque with short circuit (20% at $t=0.9\text{s}$) under load ($T_L = 3 \text{ Nm}$ at $t=0.7\text{s}$)

In the initial stage, until $t=0.9\text{s}$, the short circuit level is set to zero, representing a healthy *IM* without any faults. A load torque equal to 3Nm is applied at 0.7s . A defect is applied at $t=0.9\text{s}$ (20%). To test the severity of the fault. The fault impact appears on the stator currents (Figure 7), the speed of rotation (Figure 8) the electromagnetic torque (Figure 9), with increasing oscillations.

7.3. Influence of short circuit fault on the stator current

In what follows we present the simulation of the operation of the motor with short circuit of the turns of a coil with (10%, 20%, 30% and 50%) for each load (from 0 Nm to 5 Nm), to record the maximum values of the stator current

It can be revealed that, with the increase in the defect ratio of the affected phase (*as*) and with the increase of the load torque, the amplitude (or the max value) of the stator phase current i_{saMax} increases.

7.4. Results from the LS-SVM approach

As it has been described in section 6, the proposed monitoring methodology is developed to detect the stator winding inter-turn short circuit fault. The simulation results of proposed approach are shown in figures 11 and 12 respectively, in which 30 data are used to train the model and other 30 data are used to test its performance (Table 1).

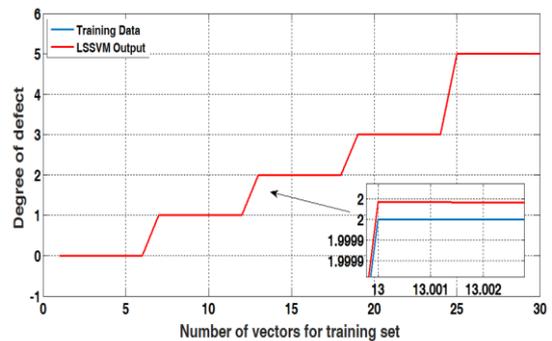


Fig. 10. Variation of degree of defect according to vector number for the training set

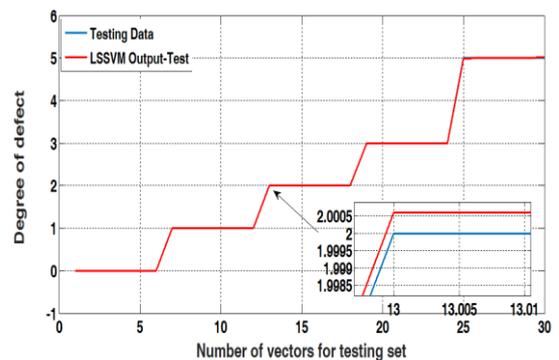


Fig. 11. Variation of degree of defect according to vector number for testing set

From Figure 10 and 11, it is very clear that the *LS-SVM* algorithm gives values that are almost identical (very good adaptation) to those desired (targets). In addition, Figure 12 (a and b) displays clearly that the errors corresponding to the training and the test are very low with higher values of absolute error of 0.0118 for testing stage.

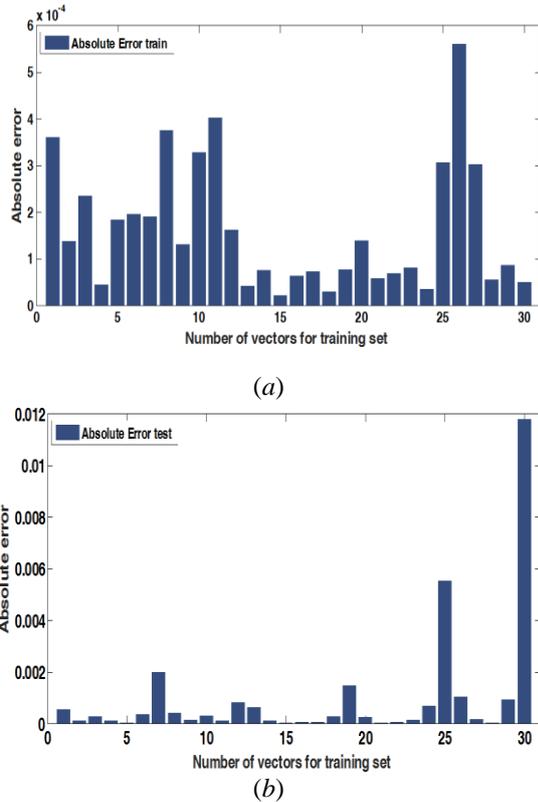


Fig.12 Curves of : a) absolute error training, b) absolute error testing

Table 2: Performance of the proposed approach

Models	RMSE _{tr}	R _{tr} ²	MAPE _{tr}	RMS _{E_{test}}	R _{test} ²	MAP _{E_{test}}
<i>LS-SVM</i>	0.0174	.9999	0.3932	.0251	.9998	0.5078
ANN	0.1010	.9966	4.6658	.0989	.9967	4.8040

Table 3: Machine parameters

value	parameters
Rs=2.89 [Ω]	Strength of a stator phase
P=2	Number of pole pairs
J=0.007[Kg.m ²]	Moment of inertia
Nr=28	Number of rotor bars
Ns=464	Number of turns
Ls=0.341 [H]	Stator inductance
Lr=0.344 [H]	Rotor inductance
Un:220/380 [V]	Nominal voltage
In: 4,3/2,5 [A]	Rated current
Nr=1425 [tr/mn]	Rated speed
Pn=1.1 [kW].	Nominal power
T _L = 7 [N.m]	Rated torque

Comparison of our proposed approach with other similar method as ANN technique is a crucial part to evaluate the performance of the diagnostic *LS-SVM* system. The comparison is listed in Table

3 using three evaluation metrics are: Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and Correlation coefficient (R²). These metrics are defined in reference [20].

As can be seen, the *LS-SVM* approach have the lowest MAPE and RMSE, and higher R² for the test set compared with ANN method.

8. CONCLUSION

In this paper, a *LS-SVM* approach has been proposed as monitoring system to detect stator winding inter-turn short circuit fault of the induction motor, in which the maximum amplitude of the stator current under different load conditions is used as input variable from motor. Due to its strong generalization capability, *RBF* kernel function is used in order to augment the generalization performance of *LS-SVM* for classification task. The simulation shows very good adaptation based on *LS-SVM* to the database used for the operation of training and testing. The proposed method could also be applied for other fault examination. To be able to distinguish other types of faults on the stator and / or the rotor, it will undoubtedly be necessary to add new parameters. The choice of these can be made by carrying out an analysis of the possible consequences that certain faults can generate. This is part of the perspectives of this study

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