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DETECTION OF STATOR WINDING INTER-TURN SHORT CIRCUIT FAULT IN INDUCTION MOTOR USING LS-SVM

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ABSTRACT

A variety of approaches have been proposed for monitoring the state of machines based on intelligent techniques such as neural network, fuzzy logic, neuro-fuzzy, pattern recognition. However, the use of LS-SVM for machine condition monitoring and fault diagnosis is still rare. For this reason, LS-SVM approach has been investigated in this study for inter-turn fault detection in stator winding of induction motor. The proposed method uses as input the stator current and decides the motor condition as output by indicating the severity of the short-circuits fault.

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

1. INTRODUCTION

Induction motors (IM) are the mainstay for every industry. However like any other machine, they will eventually fail because of heavy duty cycles, poor working environment, installation and manufacturing factors, etc. With escalating demands for reliability and efficiency, the field of fault diagnosis in induction motors is gaining importance [1-3]. The diagnosis and oversight of a device are generally passed through the knowledge of his healthy behaviour, total control of the various modes of operation is then essential when considering an advanced monitoring of the process

For this purpose, their maintenance and their diagnosis have become an economic issue. Therefore, it is recommended to detect faults early in order to remedy them in the shortest possible time to minimize the effects on the electrical installation or on the machine itself. Broadly, an induction motor can develop either internal fault or external fault. With reference to the origin, a fault may be mechanical or electrical. Fault can be classified as stator fault or rotor fault depending on the location of the fault. Faults associated with the moving parts like bearing and cooling faults are categorized as rotor faults [1-3]. Specifically, induction motor faults can be broadly classified into bearing failures, stator faults, rotor faults, air gap eccentricity, mechanical vibrations, etc. Over the recent years, there has been increasing efforts dedicated in establishing AI based models to predict real-world time-dependent data. Various AI approaches 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) approaches have been applied to cope with time series prediction in various domains [4-6]. Support vector machines have been utilized as a popular algorithm realized from the machine learning [7]. 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 converts 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 [7-8].

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 healthy squirrel-cage induction motor and modelling 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

Stator winding faults in squirrel cage induction motor are generally due to insulation failure. The stator short-circuits faults occurs, when the stator windings get shorted. The different types of stator winding faults can be classified as [12-13] : **(a)** short circuit between two turns of same phase-called turn-to-turn fault, **(b)** Short circuit between two coils of same phase-called coil to coil fault, **(c)** Short circuit between turns of two phases called phase to phase fault, **(d)** Short circuit between turns of all three phases, **(e)** Short circuit between winding conductors and the stator core-called coil to ground fault, **(f)** open-circuit fault when winding gets break.

Different types of stator winding faults are shown in Figure. 1.

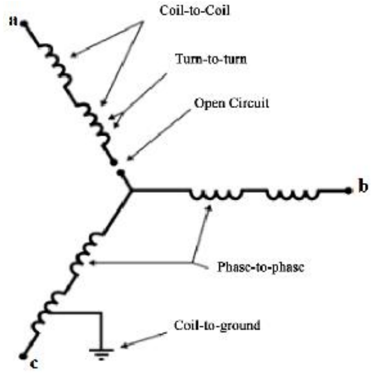


Figure1: Star-connected stator showing different types of stator winding fault [13].

3. MODELLING THE "HEALTHY" ASYNCHRONOUS MACHINE

The modelling of the induction machine is an essential and necessary phase for the various control applications, and also for the diagnosis and monitoring. The mathematical modelling allows observing and analysing different evolutions of its electrical and electromagnetic greatness [13].

3.1 Electricals equations:

The general expressions of the machine according to the flows and currents are:

$$\begin{cases} [V_{sabc}]=[R_s][i_{sabc}]+\dfrac{d}{dt}[\psi_{sabc}] \\ [V_{rabc}]=[R_r][i_{rabc}]+\dfrac{d}{dt}[\psi_{rabc}] \end{cases} \quad (1)$$

Where:

$$[V_{sabc}]=[V_{sa}\quad V_{sb}\quad V_{sc}]^T \qquad [V_{rabc}]=[0\quad 0\quad 0]^T$$

$$[i_{sabc}]=[i_{sa}\quad i_{sb}\quad i_{sc}]^T \qquad [i_{rabc}]=[i_{ra}\quad i_{rb}\quad i_{rc}]^T$$

$$[\psi_{sabc}]=[\psi_{sa}\quad \psi_{sb}\quad \psi_{sc}]^T \qquad [\psi_{rabc}]=[\psi_{ra}\quad \psi_{rb}\quad \psi_{rc}]^T$$

$$[R_s]=\begin{bmatrix} R_s & 0 & 0 \\ 0 & R_s & 0 \\ 0 & 0 & R_s \end{bmatrix} \qquad [R_r]=\begin{bmatrix} R_r & 0 & 0 \\ 0 & R_r & 0 \\ 0 & 0 & R_r \end{bmatrix}$$

3.2 Torque equations

The electromagnetic torque is given by the following equation

$$T_{em}=\frac{1}{2}[i_{sabc}]^T\left\{\frac{d}{d\theta_s}[M_{sr}][i_{rabc}]\right\} \quad (2)$$

Where

θs is the angular position of the stator

$$[M_{sr}]=M\begin{bmatrix} \cos\theta_s & \cos\left(\theta_s+\frac{2\pi}{3}\right) & \cos\left(\theta_s-\frac{2\pi}{3}\right) \\ \cos\left(\theta_s-\frac{2\pi}{3}\right) & \cos\theta_s & \cos\left(\theta_s+\frac{2\pi}{3}\right) \\ \cos\left(\theta_s+\frac{2\pi}{3}\right) & \cos\left(\theta_s-\frac{2\pi}{3}\right) & \cos\theta_s \end{bmatrix}$$

4. MODELLING OF THE ASYNCHRONOUS MACHINE "IN THE PRESENCE OF THE DEFECT":

The type of defect that will be treated in this part concerns the short circuit between turns of the same phase.

To model this defect, we will assume that a number of turns "*n*" among those of phase "*a*" is short-circuited. This section of short-circuited turns is defined by the ratio "*cc*" between the number of shorted turns and the total number of turns of the phase "*a*", which is introduced into the mathematical model governing the operation of the machine. (Figure 2) shows the 3 stator windings with short circuit. Therefore the inductance and the resistance of the faulty phase changes and the mutual inductance between this phase and all other windings of the machine [13-14]

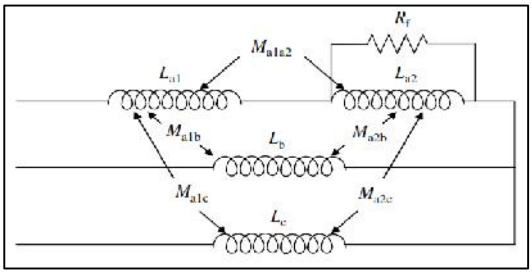


Figure 2 : Equivalent circuit of the stator winding with phase a inter-turn short circuit fault

The short-circuit fault in the stator winding causes a high current to flow in the short-circuited turns. This fault current can influence the currents of the other phases and produces a phase-to-earth and phase-to-phase short circuit, and subsequently leads to damage to the machine. [13-14]. Therefore, the detection of these defects is essential to avoid operation at dangerous conditions and reduce downtime. Modelling of the defective *IM* consists in introducing a resistance "R_f" in parallel with the short-circuited turns in the infected phase (Figure2).

A voltage will be induced in this short-circuit mesh, this induced voltage circulates a current in the short-circuited turns called fault current; the latter has a relationship of proportionality with the fault resistance and the induced voltage. The high resistance "R_f" corresponds to the case of the beginning of the deterioration of the insulation. The new form of the stator voltage equations in the natural basis frame is then rewritten as follows [14]:

$$[V_{sabc}]_f = [R_s]_f \, [i_{sabc}]_f + \frac{d}{dt}[\psi_{sabc}]_f \tag{3}$$

Where:

$$[V_{sabc}]_f = [V_{sa} \quad V_{sb} \quad V_{sc} \quad 0]^T$$

$$[i_{sabc}]_f = [i_{sa} \quad i_{sb} \quad i_{sc} \quad i_f]^T$$

$$[\psi_{sabc}]_f = [\psi_{sa} \quad \psi_{sb} \quad \psi_{sc} \quad \psi_{sd}]^T$$

$$[R_s]_f = \begin{bmatrix} (R_s - R_f) & 0 & 0 & R_f \\ 0 & R_s & 0 & 0 \\ 0 & 0 & R_s & 0 \\ 0 & 0 & 0 & R_f \end{bmatrix} \tag{4}$$

However, we keep the voltage equations of the rotor unchanged. If we denote by "cc" the fraction of the number of shorted turns of phase "*a*", then we have a healthy portion of fraction (*1-cc*) of turns and we assume phases "*b*" and "*c*" healthy. We will have the new matrix of the following stator inductors.

$$[L_{ss}] = \begin{bmatrix} L_s & M_{a1b}+M_{a2b} & M_{a1c}+M_{a2c} & -(L_{a2}+M_{a1a2}) \\ M_{a1b}+M_{a2b} & L_s & M_s & -M_{a2b} \\ M_{a1c}+M_{a2c} & M_s & L_s & -M_{a2c} \\ -(L_{a2}+M_{a1a2}) & -M_{a2b} & -M_{a2c} & L_{a2} \end{bmatrix}$$

$$[L_{ss}] = L_s \ diag \ [(1-cc) \ \ 1 \ \ 1 \ \ cc] +$$

$$M_s \begin{bmatrix} (1-cc)^2 & -\frac{1-cc}{2} & -\frac{1-cc}{2} & cc\,(1-cc) \\ -\frac{1-cc}{2} & 1 & -\frac{1}{2} & -\frac{cc}{2} \\ -\frac{1-cc}{2} & -\frac{1}{2} & 1 & -\frac{cc}{2} \\ cc\,(1-cc) & -\frac{cc}{2} & -\frac{cc}{2} & cc.^2 \end{bmatrix} \tag{5}$$

Therefore, the matrix of mutual inductances becomes:

$$[M_{sr}] = \tag{6}$$

$$M \begin{bmatrix} (1-cc)\cos\theta_s & (1-cc)\cos\left(\theta_s + \frac{2\pi}{3}\right) & (1-cc)\cos\left(\theta_s - \frac{2\pi}{3}\right) \\ \cos\left(\theta_s - \frac{2\pi}{3}\right) & \cos\theta_s & \cos\left(\theta_s + \frac{2\pi}{3}\right) \\ \cos\left(\theta_s + \frac{2\pi}{3}\right) & \cos\left(\theta_s - \frac{2\pi}{3}\right) & \cos\theta_s \\ cc\cos\theta_s & \cos\left(\theta_s + \frac{2\pi}{3}\right) & \cos\left(\theta_s - \frac{2\pi}{3}\right) \end{bmatrix}$$

Where:

L_s and M_s are the stator self and mutual inductances of the healthy machine.

L_{a2} is the self-inductance of the faulty winding a_{s2} (Figure 2). M_{a1b} and M_{a1c} are mutual inductances between a_{s2} and the windings b_s and c_s. In addition, M_{a1a2}, M_{a2b} and M_{a2c} are, respectively, the mutual inductances between a_{s2}, and the windings a_{s1}, b_s and c_s. [14].

5. LEAST SQUARES SUPPORT VECTOR MACHINES

A brief description of *LS-SVM* is presented in this section while a detailed explanation can be found in the reference [15]. The *LS-SVM* can solve the small-sample, nonlinear and high-dimensional problems, but when it is used to solve nonlinear problems, the selection of kernel function directly affects the final classification result [9-11].

Given *a* training set of *N* data points $\{y_k, x_k\}_{k=1}^{N}$, where $x_k \in R^n$ is the *k-th* input pattern and $y_k \in R$ is the *k-th* output pattern, the classifier can be constructed using the support vector method in the form

$$y(x) = sign\left[\sum_{k=1}^{N} \alpha_k y_k K(x, x_k) + b\right] \tag{7}$$

Where α_k called support values and *b* is *a* constant. $K(x, x_k)$ indicates a kernel function whose value equals the inner product of *x* and x_k vectors in the feature space $\varphi(x)$ and $\varphi(x_k)$ [10-11, 16]. The basic features of a kernel function are derived from Mercer's theorem. All function satisfies Mercer's condition is defined as kernel function. Typical examples of the kernel function are:

$K(x, x_k) = x_k^T x$ (linear).

$K(x, x_k) = (x_k^T x + 1)^d$ (Polynomial).

$K(x, x_k) = \tanh[\kappa x_k^T x + \theta]$ (Multilayer perceptron).

$K(x, x_k) = exp\{-\|x - x_k\|_2^2 / \sigma^2\}$ (RBF).

Where:

T, *d*, *K*, θ and σ are constants [9-10,16].

For example in case of two classes, the classifier is obtained as follows:

$$\begin{cases} w^T \varphi(x_k) + b \geq +1 & if \ y_k = +1 \\ w^T \varphi(x_k) + b \leq -1 & if \ y_k = -1 \end{cases}$$

This can also be written as

$$y_k [w^T \varphi(x_k)+b] \geq 1, \; k=1,...,N$$

Where $\varphi(\,)$ is a nonlinear function mapping of the input space to a higher dimensional space. *LS-SVM* classifiers\

$$\min_{w,b,e} J_{LS}(w,b,e)=\frac{1}{2}w^T w+\gamma \frac{1}{2}\sum_{k=1}^{N} e_k^2 \qquad (8)$$

Subjects to the equality constraints

$$y_k [w^T \varphi(x_k)+b] =1-e_k , \; k=1,...,N$$

The Lagrangian is defined as

$$L(w,b,e;\alpha)=J_{LS} -\sum_{k=1}^{N} \alpha_k \left\{ y_k [w^T \varphi(x_k)+b] -1+e_k \right\}$$

With Lagrange multipliers $\alpha_k \in R$ (called support values).

The conditions for optimality are given by

$$\begin{cases} \frac{\partial L}{\partial w}=0 \;\rightarrow\; w=\sum_{k=1}^{N} \alpha_k y_k \varphi(x_k) \\ \frac{\partial L}{\partial b}=0 \;\rightarrow\; \sum_{k=1}^{N} \alpha_k y_k =0 \\ \frac{\partial L}{\partial e_k}=0 \;\rightarrow\; \alpha_k =\gamma e_k \\ \frac{\partial L}{\partial \alpha_k}=0 \;\rightarrow\; y_k [w^T \varphi(x_k)+b] -1+e_k =0 \end{cases} \qquad (9)$$

For $k=1,\ldots N$. After elimination of w and e one obtains the solution

$$\begin{bmatrix} 0 & Y^T \\ Y & ZZ^T +\gamma^{-1} I \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ 1_v \end{bmatrix} \qquad (10)$$

With

$$Z=[\varphi(x_1)^T y_1 ;...;\varphi(x_N)^T y_N],$$
$$Y=[y_1 ;...;y_N], 1_v =[1;...;1],$$
$$e=[e_1 ;...;e_N]$$

and $\alpha=[\alpha_1 ;...;\alpha_N]$. Mercer's condition is applied to the matrix $\Omega =ZZ^T$ with

$$\Omega_{kl} =y_k y_l \varphi(x_k)^T \varphi(x_l) =y_k y_l K(x_k ,x_l)$$

The kernel parameters, i.e. σ for *RBF* kernel, can be optimally chosen by optimizing an upper bound on the *VC* dimension. The support values αk are proportional to the errors at the data points in the *LS-SVM* case, while in the standard *SVM* case many support values are typically equal to zero. When solving large linear systems, it becomes needed to apply iterative methods [10].

The RBF kernel function is usually employed as the kernel function. In this study, RBF kernel was opted for *LS-SVM* inter-turn fault detection.

The *RBF* width σ^2 and regularization parameter γ, which affect *LS-SVM* generalization performance should be carefully selected [15-16].

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 3).
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:

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

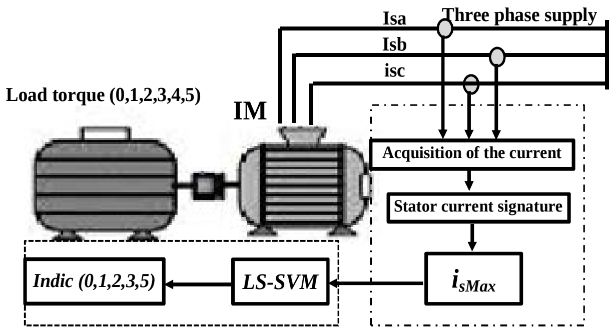


Figure 3: Block diagram of LS-SVM for stator winding short-circuit fault diagnosis

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 *5.5Nm* 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*).

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 (ias) and decides the motor condition as output by indicating the severity of the short-circuits fault.

Table 1: Database for training and testing

cc %	Training set		Testing set		
	T_L	*Input Max(ias)*	T_L	*Input Max(ias)*	*Indication (indic)*
0%	0	3,5574	0.5	3,5602	0
0%	1	3,5775	1.5	3,6086	0
0%	2	3,6537	2.5	3,7123	0
0%	3	3,7841	3.5	3,8684	0
0%	4	3,9647	4.5	4,0722	0
0%	5	4,1903	5.5	4,3184	0
10%	0	9,5708	0.5	9,7547	1
10%	1	9,9494	1.5	10,1347	1
10%	2	10,3357	2.5	10,5335	1
10%	3	10,7400	3.5	10,9522	1
10%	4	11,1699	4.5	11,3933	1
10%	5	11,6228	5.5	11,8587	1
20%	0	18,0303	0.5	18,2184	2
20%	1	18,4315	1.5	18,6132	2
20%	2	18,8375	2.5	19,0337	2
20%	3	19,2530	3.5	19,4834	2
20%	4	19,7235	4.5	19,9746	2
20%	5	20,2383	5.5	20,5166	2
30%	0	26,7037	0.5	26,8866	3
30%	1	27,1105	1.5	27,2743	3
30%	2	27,5216	2.5	27,6961	3
30%	3	27,9371	3.5	28,1595	3
30%	4	28,4147	4.5	28,6888	3
30%	5	28,9864	5.5	29,3148	3
50%	0	44,1895	0.5	44,3518	5
50%	1	44,6003	1.5	44,709	5
50%	2	45,0148	2.5	45,1097	5
50%	3	45,4332	3.5	45,5751	5
50%	4	45,8556	4.5	46,1498	5
50%	5	46,5135	5.5	46,9782	5

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: γ=1000, σ^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 *Tr = 3 Nm* at the moment *0.7s*

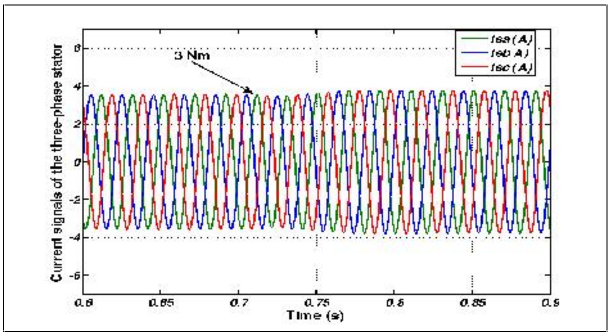


Figure.4: Stator current of the healthy motor under load (T_L = 3 Nm at t=0.7s)

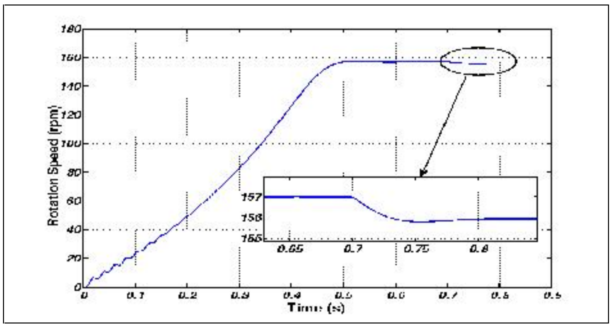


Figure 5 : Speed of rotation of the healthy motor under load (T_L = 3 Nm at t=0.7s)

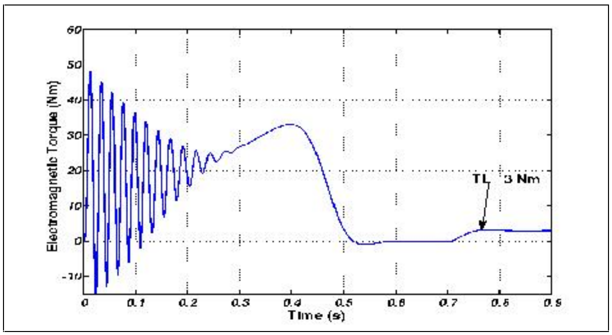


Figure 6 : Electromagnetic torque of the healthy motor under load (T_L = *3 Nm at t=0.7s*)

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*.

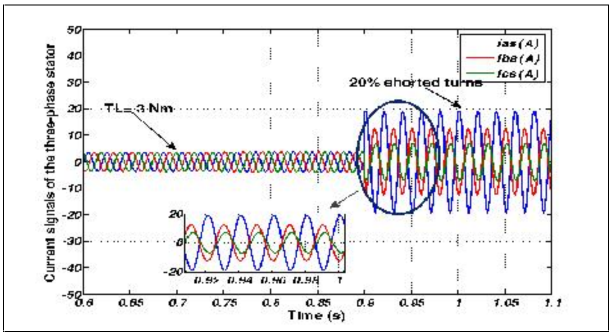


Figure 7 : Stator current motor with short circuit (*20% at t=0.9s*) under load (T_L = *3 Nm at t=0.7s*)

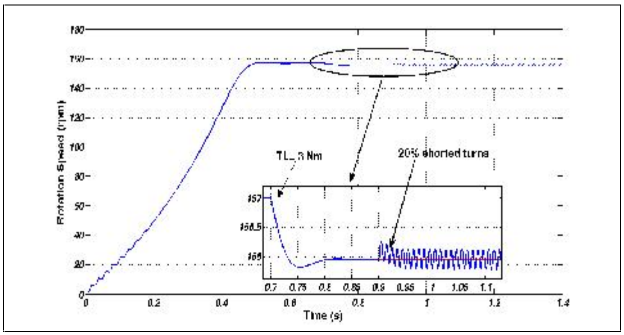
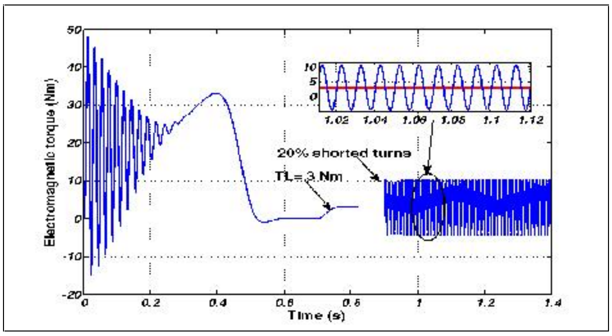


Figure 8 : Speed of rotation with short circuit (*20% at t=0.9s*) under load (T_L = *3 Nm at t=0.7s*)



. Figure 9 : Electromagnetic torque with short circuit (*20% at t=0.9s*) under load (T_L = *3 Nm at t=0.7s*)

In the initial stage, until *t=0.9s*, the short circuit leve is set to zero, representing a healthy *IM* without any faults. A load torque equal to *3Nm* is applied at *0.7s*. A default is applied at *t=0.9s* (*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 descripted 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).

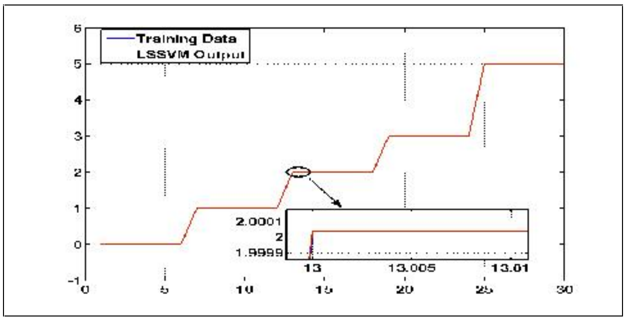


Figure 10 : Variation of degree of defect according to vector number for the training set.

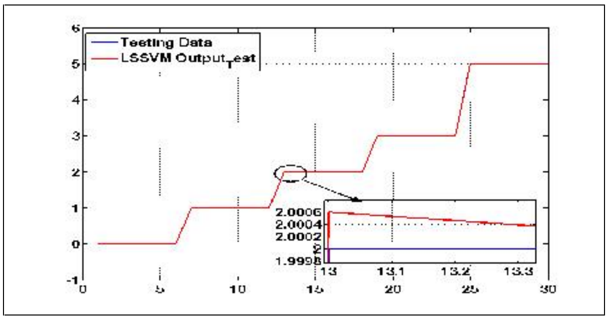
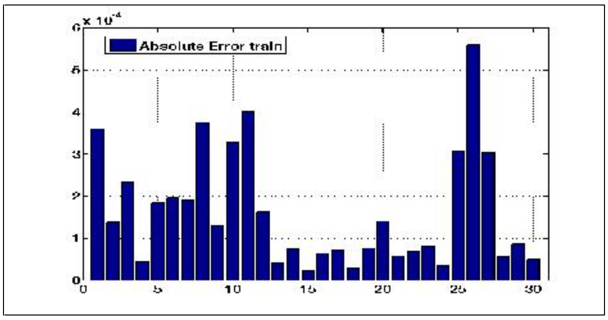
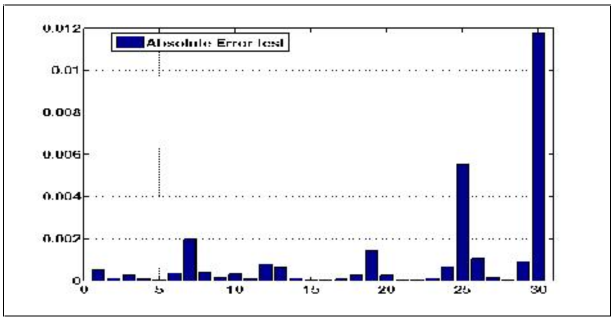


Figure 11: Variation of degree of defect according to vector number for testing set.

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.



(*a*)



(*b*)

Figure 12 : Curves of : a) absolute error training

b) absolute error testing

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.

Machine settings

Rs=2.89 [Ω] Strength of a stator phase

P=2 Number of pole pairs

J=0.007 [Kg.m2] Moment of inertia

Nr=28 Number of rotor bars

Ns=464 Number of turns

Ls=0.341 [H] Leakage inductance of a stator phase

Lr=0.344 [H] Leakage inductance of a stator phase

Un: 220/380 [V] Nominal voltage

In: 4,3/2,5 [A]. Rated current

Nr=1425 [tr/mn]. Rated speed

Pn=11 [kW]. Nominal power

Cn= 7 [N.m] Rated torque

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