ISSN: 0976-3104

FAULT DIAGNOSE OF INDUCTION MOTOR USING NOVEL LEAST SQUARE FUZZY TOTAL MARGIN SUPPORT VECTOR MACHINE

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ABSTRACT

Induction motor plays an extremely vital part in the industrial developments due to its more reliable and regular integration in the commercial instruments and numerous applications. In regular situations, its process is reliable, however in irregular situations its process gets faults which can generate huge undesirable losses. To diagnose the faults in induction motors, a novel least square fuzzy total margin support vector machine (LS-FTM-SVM) is utilized. For stationary signals and non-stationary signals, Wavelet Packet Transform (WPT) is utilized to detect and extract the fault feature vectors. LS-FTM-SVM classifies the induction motor. This proposed method, LS-FTM-SVM is solved set of linear equations, and is computationally less intensive than other SVM methods.

KEY WORDS
Energy coupling, wireless parameters.

Published: 2 December 2016

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INTRODUCTION

The fault diagnosis of induction motor is great importance in production lines. This method can consider the maintenance cost and the some failures by allowing the fault detection of catastrophic faults [1]. A fault is defined as any types of malfunction of components, which may occur in a system and fault will reduce the performance of the system. Fault detection is the process which may be instructed as something is a problem in the system and needs to be repaired. The fault isolation is detected which fault occurs among the possible faults.

Induction motors are one of the most broadly used machines on which, depending on the industrial production process. Faults of these vital equipments can cause financial loss to the production plans which stimulate the researchers to consider and improve the efficient fault diagnosis systems for these rotary equipments [2]. In our work, the fault diagnosis of induction motors has been proposed which is classified as namely model based, signal based and data based. Induction motors are generally used in rotary machinery systems may be included machinery parts and used some industrial applications due to their arrogance, the maintenanace cost is low and need low maintenance requirements [3]. The induction motors are well designed faults to be inherent due to the stresses involved in the conversion of electrical energy to mechanical energy and vice versa. The faults of induction motors may not only cause of interference of product operation, but also raise the cost, reduce the product quality and effect safety of operators.

Our method of detection faults can reduce the breakdown and minimize the maintenance time. The machine availability and reliability can be increased in the same time. In regular situations, its process is reliable, however in irregular situations its process gets faults which can generate huge undesirable losses. To diagnose the faults in induction motors, a novel least square fuzzy total margin support vector machine (LS-FTM-SVM) is utilized. Wavelet Packet Transform (WPT) is used to determine and extract the fault feature vectors in the stationary and non-stationary signals. Our proposed technique divides the induction motor. This proposed method of LS-FTM-SVM is explained some linear equations, and is computationally less intensive than other SVM methods.

BASICS OF SVM CLASSIFIER

The SVM has performed well even when it was used to solve the nonlinear problems with high dimensions with small training samples. The SVM classifier is better one compared than ANN classifier. The ANN classifier has the principle of risk minimization. In ANN, conventional empirical risk minimization is used to reduce the error on training dataset. But in SVM classifier, the risk minimization is used to decrease the upper bound of the expected risk. The SVM is based on statistical learning theory and it is a learning machine [4]. The SVM can be stated as follows: first map the input vectors into the features, space and it's have higher dimension which is relevant with to the kernel function. In the first step, the feature space is obtained and it's designed a hyperplane which separates two classes. This approach can be continued to multi-class problems.

The SVM has been successfully applied in many fields, including classification, recognition, regression analysis and forecast. It gives a unique solution and strongly regularized method suitable for ill-posed problems. The SVM is used to detect the optimal hyperplane by reducing the upper bound of the generalization error and it will be increasing the distance, margin, hyperplane and the data [5]. The SVM uses the preprocessing strategy in learning by mapping input space X to a high-dimensional feature space F. The fault diagnosis is basically a kind of pattern recognition method used in practical applications. There

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is a given sample set G= {(*xi*, *yi*), *i* = 1.1} each sample $x_i \epsilon R^d$ Belongs to a class by $y\epsilon\{+1,-1\}$. The boundary can be expressions are given below:

$$\omega x + b = 0$$

Where ω is a weight vector and *b* denoted by bias. The decision function can be used to categorize any data point in either class 1 or 2:

$$f(x) = sgn(wx + b)$$

The optimal hyperplane dividing the data can be found as a solution to the following constrained optimization problem:
Minimize

$$\frac{1}{2}\|\omega\|^2$$

Subject to

$$y_i[(\omega x_i) + b] - 1 \geq 0, i = 1,1$$

Introducing Lagrange multipliers a_i≥0, the optimization can be written as,
Maximize

$$L(\omega, b, a) = \sum_{i=1}^{l} a_i - \frac{1}{2}\sum_{ij=1}^{i} a_i a_j y_i y_j (x_i x_j)$$

Subject to

$$a_i \geq 0$$

$$\sum_{i=1}^{i} a_i y_i = 0$$

The decision function can be found as follows:

$$f(x) = sgn\left(\sum_{i=1}^{l} a_i y_i (x_{i,} x) + b\right)$$

If the input linear boundary space is not enough to divide into two classes properly. In the higher dimension, the boundary will produce a hyperplane which may be allows linear separation.

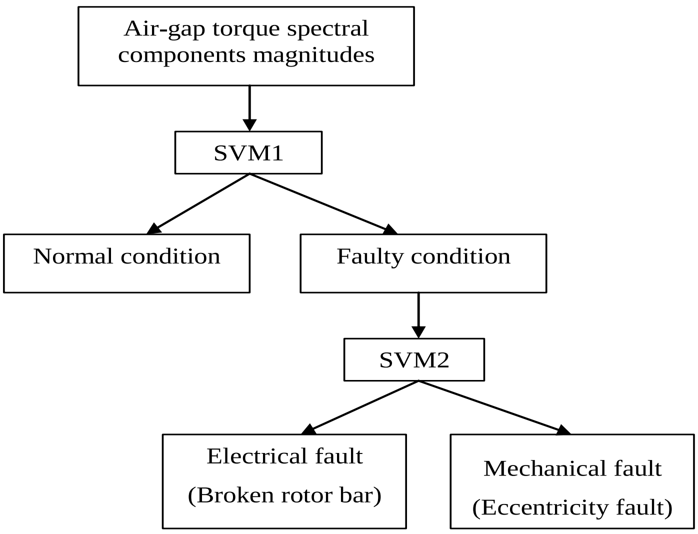

Fig. 1: Shows SVM classifiers based on Induction motor fault diagnostic model.

The SVM is accomplished by using a transformation Φ(*x*) is to mapping the data from the input space to feature space. The kernel function can be defined as,

$$K(x, y) = \phi(x)\phi(y)$$

The above equation can be mentioned the kernel functions are used in linear functions, polynomial functions, radial functions, radial basis and signed functions. The Advantages of SVM is to produce the accurate classifiers, less over-fitting and robust to noise. The disadvantage of SVM is a binary classifier and it can be used in multi-class classification, pairwise classifications [6]. The SVM classifier is computationally expensive and it will be running slow.

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ISSN: 0976-3104

PROPOSED WORK

An LS-FTM-SVM modeling method, as indicated in [Fig.. 2] is improved for time varying, nonlinear processes across multiple working region. This method combines the advantage of local LS-FTM-SVM modeling and global regularization and it captures the local dynamics in each working region [7] [8]. The global regularization is used to reduce the global error. This technique may secure the continuity and smoothness between the LS-FTM-SVM models and avoid the over-fitting of our method. Thus, the method improved here may effectively complex processes across the multiple region.

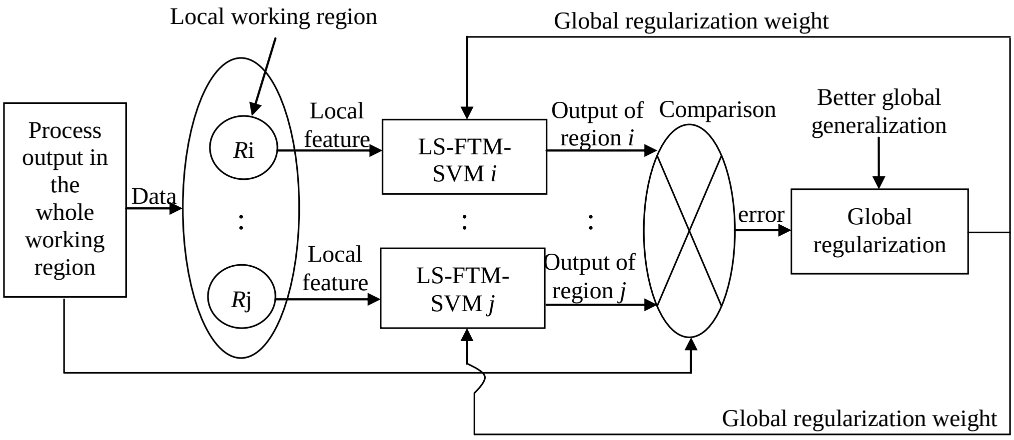

Fig. 2 : Novel LS-SVM modeling method.

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Pseudo code of the LS-FTM-SVM algorithm

A useful classifier called LS-FTM-SVM classifier is proposed in our paper. In our work, a binary classification problem is represented by $\{(r_1, y_1), (r_2, y_2), \ldots, (r_L, y_L)\}$, where $r_i \in \{-1, 1\}$ denotes an *n*-dimensional data points, for $i = 1, 2, \ldots, L$. The input is given by,

D= $\{R, Y\} = \{r_i, y_i\}_{i=1}^{L}$ is the training set (1)

The training set divides into two sets are namely as the fuzzy positive training set S_f^+ and the fuzzy negative training set S_f^-.

The above set following as:

$S_f^+ = \{r_i, y_i\}_{i=1}, \ldots, L_p + 1, \ldots, L_p + L_n$ and $L_p + L_n = L$. (2)

Fuzzification of the training set is follows:

$$\mu_i^+ = f_{lin}^{cen}(r_i),\ \mu_i^- = f_{lin}^{cen}(r_i)\ q$$

(3)Choose *i* such that

$$\mu_i^+ C_2^+ < \mu_i^+ C_1^+ \text{ and } \mu_i^- C_2^- < \mu_i^- C_2^- \quad (4)$$

In the above equation (4), the C_1^+ and C_1^- are the weights for positive and negative surplus variables, respectively. The restrains for this maximization problem are the same as those in the dual form of the linear case. By means of taking the mean value of b^*, we can estimate the optimal value of b^* can follow:

$$b^* = \frac{L_p \Sigma_{r_i \epsilon A_f} + \Sigma_{j=1}^{L} a_j y_j k(r_i, r_j) + L_n \Sigma_{r_i \epsilon A_f^-} \Sigma_{j=1}^{L} a_j y_j K(r_i, r_j)}{-L_p L_n} \quad (5)$$

Calculate

$$\Sigma_{i=1}^{L} a_i y_i K(r_i, r) + b^* \quad (6)$$

Where A_f^+ and A_f^- are the subsets of S_f^+ and S_f^-, respectively.

Global regularization and parameter optimization

In our proposed method, the global regularization employed in the LS-FTM SVM techniques. Given an input training set $\{x_{ij}, y_{ij}\}_{i=1, j=1}^{k,n}$, where x_{ij} and y_{ij} Are the *get* input and *I* is the output of the local working region, respectively, the optimization problem may be written as:

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$$\min_{\omega,\omega_i,e_{ij}} \sum_{i=1}^{k}\left(\frac{R_i}{2}||\omega_i||^2\right) + \sum_{i=1}^{k}\left(\frac{\lambda_i}{2}||\omega_i-\omega||^2\right) + \sum_{i=1}^{k}\left(\frac{\gamma_i}{2}\sum_{j=1}^{n} e_{ij}^2\right)$$

$$y_{ij} = \omega_i^T \varphi i(x_{ij}) + b_i + e_{ij}, j = 1, \dots, n; i = 1, \dots, k \qquad (7)$$

Where e is the modeling error; ω is the global weight vector; $\sum_{i=1}^{k}\frac{R_i}{2}\|\omega_i\|^2$ denotes the local regularization that assures the generalization and over-fitting the proposed LS-FTM SVM model in each local region [9].
The proposed model has the following advantages:
1. This method recognizes the local dynamics.
2. The proposed method also locates the interaction between the adjacent local regions and develops the local and global generalization.
3. The method reduces the global error.
In this work, the local and global weight vectors are optimized. The linear SVM classification method is used to transform the optimization problem into a convex optimization problem. This problem can be easily solved by using the proposed method. Let $v_i = \omega_i - \omega$, such that $\omega_i = v_i + \omega$. The global optimization problem can be written as

$$\min_{\omega,v_i,e_{ij}} \sum_{i=1}^{k}\left(\frac{R_i}{2}||\omega+v_i||^2\right) + \sum_{i=1}^{k}\left(\frac{\lambda_i}{2}||v_i||^2\right) + \sum_{i=1}^{k}\left(\frac{\gamma_i}{2}\sum_{j=1}^{n} e_{ij}^2\right)$$

$$y_{ij} = (v_i + \omega)^T \varphi i(x_{ij}) + b_i + e_{ij}, \quad j = 1, \dots, n; i = 1, \dots, k \qquad (8)$$

In the above equation (7), R, λ and γ are regularization parameters and $\sum_{i=1}^{k}\left(\frac{\gamma_i}{2}\sum_{j=1}^{n} e_{ij}^2\right)$ is the mentioned the global error which is to minimize the entire working region.
Define

$$\tilde{\omega} = [\sqrt{R_1}(v_1+\omega)^T, \dots, \sqrt{R_k}(v_k+\omega)^T, \sqrt{\lambda_1}v_l^T, \dots, \sqrt{\lambda_k}u_k^T]^T \qquad (9)$$

$$\tilde{r}_{ij} = \left[0^T, \dots, \frac{x_{ij}^T}{R_i}, \dots, 0^T, 0^T, \dots, \frac{x_{ij}^T}{\sqrt{\lambda_i}}, \dots, 0^T\right]^T \qquad (10)$$

Where the *i* th and (*k*+*i*) th components of $\frac{r_{ij}^T}{\sqrt{R_i}}$ and $\frac{r_{ij}^T}{\sqrt{\lambda_i}}$ respectively.
The equation (7) mentioned optimization problem that may be converted into convex optimization problem follows:

$$\min_{\tilde{\omega},e_{ij}} J(\tilde{\omega}, e_{ij}) = \frac{1}{2}||\tilde{\omega}||^2 + \sum_{i=1}^{k}\left(\frac{\gamma_i}{2}\sum_{j=1}^{n} e_{ij}^2\right)$$

$$y_{ij} = \tilde{\omega}^T \tilde{\varphi}_i(\tilde{x}_{ij}) + b_i + e_{ij}, j = 1, \dots, n; i = 1, \dots, k \qquad (11)$$

To solve the optimization equation, a Lagrangian may be written as:

$$\Gamma(\tilde{\omega}, b_i e_{ij}, a_{ij}) = J(\tilde{\omega}, e_{ij}) - \sum_{i=1}^{k}\sum_{j=1}^{n} a_{ij}\{\tilde{\omega}^T\tilde{\varphi}(\tilde{x}_{ij}) + b_i + e_{ij} - y_{ij}\} \qquad (12)$$

Where a_{ij} denotes the Lagrange multiplier. The conditions are,

$$\frac{\partial\Gamma}{\partial\tilde{\omega}} = 0, \frac{\partial\Gamma}{\partial b_i} = 0, \frac{\partial\Gamma}{\partial e_{ij}} = 0, \frac{\partial\Gamma}{\partial a_{ij}} = 0. \qquad (13)$$

The kernel function is applied by output equations. From the above equation, the resulting of proposed model for function estimation is

$$f(x) = \sum_{i=1}^{k}\sum_{j=1}^{n} a_{ij}\, y_i k(\tilde{r}, \tilde{r}_{ij}) + b^* \qquad (14)$$

Here, $\tilde{x} = \left[0^T, \ldots, \frac{x^T}{\sqrt{R_i}}, \ldots, 0^T, 0^T, \ldots, \frac{x^T}{\sqrt{\lambda_t}}, \ldots, 0^T\right] T;$ then *i* th an *(k+i)* th components of $\frac{x^T}{\sqrt{R_i}}$ and $\frac{x^T}{\sqrt{\lambda_t}}$ respectively. In above, *x* denotes the *i* th region, the other components are zero.

By solving this equation using the proposed LS-FTM-SVM technique, the output *f(x)* can be obtained. Our proposed method is solved set of linear equations, then it is computationally less intensive and to improve the modeling accuracy of a strongly nonlinear system compared other SVM methods.

RESULTS

In this section, LS-FTM-SVM classifier is used to get fault diagnosis result. LS-FTM_SVM classifier methods require training data sets that are produced using real time simulator. In this work, totally 1365 training data sets are used for training LS-FTM-SVM classifier network. Twelve different fault modes and fault free modes are diagnosed using binary classifiers. The deviation of the testing data from training data is the maximum available within the upper and the lower bounds of the training data set. Totally 428 data sets are used for the testing. In our proposed method is compared with some other local classifier [10] [11]. The architecture and neuron number are designed to achieve high accuracy classification using neural networks. The performances of two classifiers are compared. [Fig. 3] mentioned block diagram of the proposed model.

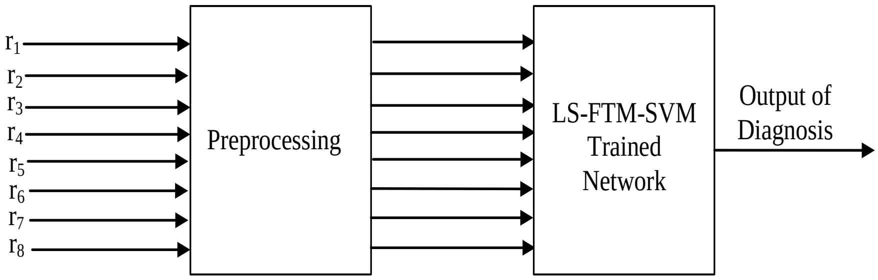

Fig. 3: Block diagram of fault diagnosis using LS-FTM-SVM classification.

Our proposed model used for diagnosing the faults, are prone to concern and practical noises. The uncertainties are due to recognizing fault free model and mathematical equations are possible for practical system. The measurement system has also uncertainty and noises. So, the performance of the proposed method needs to be verified in the presence of noises. The distributed random noise is added during testing and training is done in the absence of noise. The testing data is added with uniformly distributed random noise U(-a,a). The magnitude value of 'a' is 5%, 10%, and 20% of the testing value of the absence of noise. The fault diagnosis performance of classifiers is shown in Table.1. It can be noticed from the LS-FTM-SVM based classifier has better accuracy and more robust against noises than the some other classifiers.

Table1: Performance of the proposed classifier

Percentage of Noise	Motor Speed (rpm)	Number of Testing data	Diagnosed Data using LS-FTM-SVM	Diagnosed Data using neural network	Diagnosis Accuracy (%)	
					Local LS-SVM	LS-FTM-SVM
20	200	426	419	412	94.8	94.4
10	400	426	416	410	94.3	96.7
5	700	426	411	403	96.6	98.5
0	900	426	408	382	87.9	99.8

CONCLUSION

This paper discusses the classifier based fault detection and diagnosis schemes of system by classifying the residual patterns. SVM is a new machine-learning tool for classification, which is powerful for the practical problem with complex system machines. Our proposed method used to diagnose and detect the faults in the induction motor. And also our method is to improve the diagnosis accuracy is compared to some other SVM classifier. The Table.1 mentioned above the percentage of noise is increased and the

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diagnosis accuracy will be decreased. The diagnosed fault accuracies have estimated at motor speed 200rpm, 400rpm, 700rpm and 900rpm respectively. The results indicate that the proposed LS-FTM-SVM model can be used in diagnosing induction motor faults.

CONFLICT OF INTEREST
There is no conflict of interest.

ACKNOWLEDGEMENTS
None

FINANCIAL DISCLOSURE
None

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