J. Electrical Systems 20-3 (2024): 1942-1949

[1] Om Prakash Yadav
[2]Rajeev Kumar Chauhan
[3]Rishi Asthana
[4] Nitin S. Patil
[5]B. Suresh Babu

A Realistic Method for Diagnosing Bearing Faults of Three-Phase Induction Motor using Advanced Support Vector Machine Algorithm

Journal of Electrical Systems

Abstract: - Bearings are one of the most crucial components of any induction motor. The faults or failure of bearings can lead to high maintenance and operational costs. To ensure the induction motor operates consistently, it is crucial to identify and diagnose bearing faults at an early stage. In this perspective, this manuscript presents a method based on least square support vector machine (LSSVM) to identify the bearing defects of an induction motor. The IM parameters, such as stator currents, input voltage, and rotor speed, were extracted using experimental setup at different loads and health conditions of bearing. Then these parameters were used to train and validate the LSSVM algorithm in MATLAB to diagnose the bearing defects. The proposed method provides 97.14% fault prediction accuracy with an RBF kernel.

Keywords: Bearing Faults, Induction Motor, LSSVM, MATLAB 7.6.0., Gaussian RBF Kernel, Polynomial Kernel

I. INTRODUCTION

Induction motors are a popular kind of electric machine utilized in both industrial and residential environments because of their robust design and low maintenance requirements. The incipient fault detection and diagnosis is a crucial part that helps engineers to take necessary action before it causes a secondary faults and failure in induction motor. The primary component of electrical machines that allows the rotor to spin smoothly and maintain a fixed distance from the stator is the bearing. According to the IEEE-IAS survey study, there is a 44% chances of a bearing failing, compared to a 26%, 8%, and 22% chance of stator winding, rotor bar, and other part failure [1]. Comparably, the ABB study reports respectively 51%, 16%, 5%, and 28% of these failures, while the EPSI survey reports 41%, 36%, 9%, and 14% of bearing, stator winding, rotor bar, and other problems [1]-[3]. As a result, it may be inferred from the analysis of survey data that, when compared to other induction motor components, bearings are the most prone to faults or failures [4]. Consequently, the identification and diagnosis of bearing faults has emerged as the main area of study for scholars. Small and medium-sized machines often employ rolling-element bearings, generally referred to as anti-friction bearings, whereas high powered machines typically use sleeve (or fluid-film) bearings [5].

Excessive stress, corrosive conditions, mechanical wear, and incorrect application are other frequent reasons of bearing failures [7]. The most frequent causes of bearing failures are lubrication loss and contamination [6]. The majority of these malfunctions begin with single point defect, if not diagnosed then expanded to complete shutdown of IM [8]. This paper studies and diagnose rolling element bearing faults in details. Acoustic analysis, temperature monitoring, wear debris analysis, shock pulse method, stator current monitoring, and vibration analysis are some of the signals that can be utilized to identify bearing defects [8][9]. Because vibration signal monitoring has a direct correlation with bearing failures, it is the most chosen methodology among others [10]. Vibration measurement is one of the most effective techniques for large size induction motor but it is not suitable of small size machines as it is difficult and expensive to detect vibration signal [5][6]. So the research has tends toward other signal extraction methods like electrical parameters as stator current, input voltage etc. The sensors used to extract these electrical signals are comparatively economical and convenient.

[1] *Associate Professor, Electrical Engineering Department, Sandip Institute of Technology and Research Centre, Nashik, Maharashtra, India, Email:opnit05@gmail.com
[2]Electronics and Communication Engineering Department, IIMT College of Engineering, Greater Noida, Uttar Pradesh, India
[3]Director and Professor, Electrical Engineering Department, Goel Institute of Technology and Management, Lucknow, Uttar Pradesh, India
[4]Head and Dean Academics, Electrical Engineering Department, Sandip Institute of Technology and Research Centre, Nashik, Maharashtra, India,
[5]Professor, Electrical Engineering Department, Sandip Institute of Technology and Research Centre, Nashik, Maharashtra, India

Time-domain, frequency-domain, and time-frequency-domain techniques are frequently employed [11] methods to analyze bearing defects. To overcome the problems associated with frequency spectrum analysis of signals the research has tends toward the application of intelligent techniques as they can give better result for ambiguity and noisy data [12] [13]. Fuzzy logic technique, artificial neural network, SVM, random forest, and KNN are some common techniques that are used to analyze the extracted signal to identify bearing defects [14] [15]. SVM is the state-of-the-art classification method introduced in 1992 by Boser, Guyon, and Vapnik [16]. A detailed description of SVM has been given by Hsu and team [17]. Widodo introduced a wavelet-based nonlinear support vector machine (SVM) kernel to investigate transient current for the purpose of multiclass machine fault classification [18] [19]. To identify faults associated to bearings, a multiclass support vector machine and wavelet analysis has been incorporated to optimize signal decomposition levels [14]. An adequate scheme for selecting training parameter has been given by Rojas [20]. One of the SVM's drawbacks is that not all data types can benefit from its performance [21]. The Least Squares Support Vector Machine (LS-SVM) solves the issue with the basic SVM technique [22]. The quadratic loss function and equality constraints are used in place of the non-sensitive loss function and inequality constraints in LS-SVM. While LS-SVMs do not produce sparse solutions like SVMs do, they do find an optimization solution quickly, and pruning techniques can be used to increase the scarcity with ease [21]. In this paper, the LS-SVM approach has been applied to detect the bearing issues of induction motor.
The remaining part of the research paper is divided into five sections: section II discusses the various causes of rolling element faults, while section III provides a methodological description of the proposed research work. The mathematical analysis of Least Square Support Vector Machine is presented in Section IV, and the result and discussion are shown in Section V. Section VI presents the research's conclusion in its final form.

II. Causes of Faults in Rolling Element Ball Bearing

The causes of bearing failures include corrosive conditions, excessive loading, lubricant loss or contamination. The bearing materials become contaminated by dirt and other foreign objects that are frequently found in an operational environment [3]. These tiny particles can range in hardness from somewhat soft to diamond-like, and because of their abrasive nature, the balls and raceways wear measured amounts due to pitting and sanding. Water, acids, worn-out lubricant, and even sweat from haphazard handling during installation can all cause bearing corrosion [7]. Friction between the spinning parts of the bearing caused by lubrication loss will intensify the heating effect. The grease degrades due to the overheating, hastening the secondary failure [8]. Any type of bearing fatigue enhances the friction between ball and raceway that causes heating. If it not detected and repaired that complete bearing failure may happens. The various components of rolling element ball bearing is shown in figure 1.

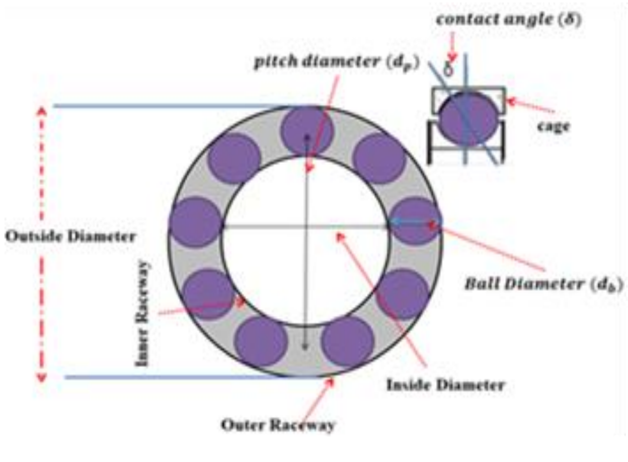

Fig.1. Components of rolling element ball bearing

III. Methodology used to Diagnose Bearing Health Conditions

The purpose of the laboratory experiment was to gather information about bearing fatigue such as lubrication loss, and tear in its material. Power analyzers and tachometers were used to extract the electrical parameters as stator current and input voltage, and speed of rotor related to healthy and faulty bearing. Precautions were taken during experimental work to avoid the damage of bearing and other components.

An induction motor with a three-phase squirrel cage was used for this experimental work. The experimental setup is shown in Figure 2. The rating of induction motor used in this experiment work is given as: 4.96A, 50 Hz, 440V, 5 HP, delta-connected, squirrel-cage induction motor with four poles. The three phase stator currents, input voltage and rotor speed were measured in this experimental work. The methodology used to identify bearing defects is shown in figure 3. The extracted datasets of IM such as stator currents IR, IY, and IB, input voltage, and rotor speed were used to train the proposed SVM algorithm and the results were verified in terms of accuracy of the result.

Fig.2. Experimental Setup to extract features of bearing health conditions

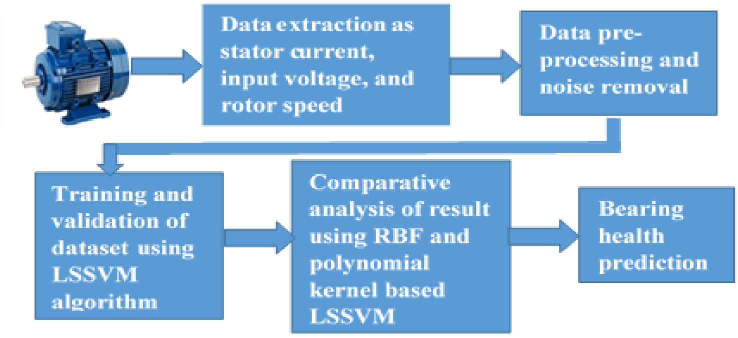

Fig. 3. Methodology used to identify bearing defects

IV. LEAST SQUARE SUPPORT VECTOR MACHINE (LS-SVM) BASED FAULT DETECTION ALGORITHM

Suppose a given training set $\{x_k, y_k\}_{k=1}^{N}$ with input data $x_k \in R^N$ and corresponding binary class labels $y_k \in \{-1, +1\}$, where N is the dimension number of input space, the SVM classifier, according to Vapnik's original formulation, linear separable data satisfies the following conditions [16][19]:

$$w^T\varphi(x_k) + b \geq 1 \quad \text{if } y_k = +1 \qquad (1)$$

$$w^T\varphi(x_k) + b \leq -1 \quad \text{if } y_k = -1 \qquad (2)$$

Where yi= +1 belong to class1 and -1 belong to class2, w^T is weighting vector that defines the direction of separable hyper plane and b is a scalar known as bias that defines the hyper plane's distance from the origin, φ is the map from the input space to the feature space .

The separating hyper plane that has the maximum distance between the hyper-plane and the nearest data, i.e. the maximum margin, is called the optimal separating hyper-plane. An example of optimal separating hyper-plane of two datasets is presented in Figure 4 [16]. According to [19] [23] [24] separating hyper-plane classifies a set of data with a margin of $\frac{2}{\|w\|}$. To put the classifying margin maximum, the value of $\|w\|^2$ should be minimum.

The optimization problem using LS-SVM model is as follows [14]

$$\min_{w,b,e} J(w,e) = \frac{1}{2}w^T w + \frac{1}{2}\gamma \sum_{k=1}^{N} e_k^2 \qquad (3)$$

Subject to equality constraint

$y_k = w^T \varphi(x_k) + b + e_k$, k=1, 2….N Where parameter γ is similar to parameter C of SVM, which is used to control function $J(w, e)$. In order to solve the optimization problem, the Lagrangian function is introduced as follows [14]:

$$L(w,b,e;\alpha) = J(w,e) - \sum_{k=1}^{N} \alpha_k \{w^T \varphi(x_k) + b + e_k - y_k\} \quad (4)$$

α_k is Lagrangian multiplier.

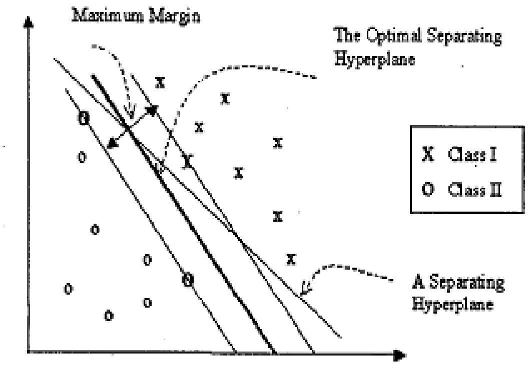

Fig. 4. Optimum hyper plane in SVM algorithm

The resulting LSSVM model for function estimation can be expressed as [21]

$$y(x) = \sum_{k=1}^{N} \alpha_k K(x, x_k) + b \quad (5)$$

Here, $K(x, x_k)$ is kernel function.

In this problem Polynomial kernel has been used due to its excellent classification performance. The Polynomial Kernel function [21] is given as

$$K(x, x_j) = ((x.x_j) + \theta)^d \quad (6)$$

where d=1,2,…..

V. Results and Discussion

In this work three phase stator currents, input voltage and rotor speed were measured at different loads and health status of bearing. Then, the extracted datasets were refined and optimized by removing unnecessary, duplicate, and inconsistent datasets. After that the optimized datasets were collectively used to train the LSSVM algorithm for accurate analysis of bearing faults.

The three phase stator currents IR, IY and IB were shown in figure 5 and figure 6 for healthy and faulty bearing with less lubrication and fatigue on inner raceway respectively. From comparative analysis, it is depicted that stator current fluctuation in IM having faulty bearing is more rather than healthy bearing. The fluctuation in stator current is due non uniform flux generation due to defects on inner raceway of bearing. The figure also depicts that IM extract more current with bearing having lubrication issue due to friction loss.

The rotor speed and input voltage in healthy and faulty IM is shown by figure 7 and figure 8. The results of figure shows that the rotor speed continuously decreases with increase in friction between balls and raceway due to fatigue in surface of bearings. As lubrication decreases the friction loss also increases. This is also one of the reason for decline in rotor speed. Figure 9 demonstrates the stator current as IR, IY, IB, input voltage and rotor speed of IM using radar graph.

After cleaning the data, the three stator currents IR, IY, and IB, input voltage V, and rotor speed were used to train the LSSVM algorithm in MATLAB 7.6.0 environment. Total 345 samples have been collected for healthy and unhealthy bearings of machine. Out of these samples, 210 samples were used to train the model and 135 samples were used to test its accuracy. Utilizing the cross-valid cost function and grid search technique, the LSSVM parameters were trained to yield an excellent result. The training result of mapping the dataset using LSSVM algorithm is shown in figure 10. The gamma value obtained was [1.6955 2.7631], the bias value was [0.5710 -0.5607], and the elapsed time was 0.062930 seconds. The result of LSSVM was compared using polynomial and

RBF kernel function and result shows that RBF kernel provides 97.14% success rate in comparison to polynomial kernel as 94.97 accuracy.

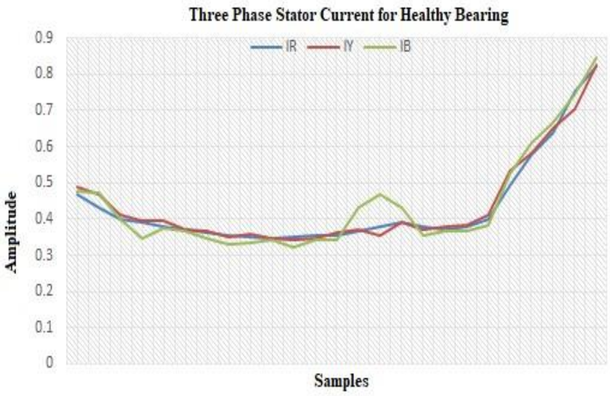

Fig.5. Three phase stator currents in healthy IM

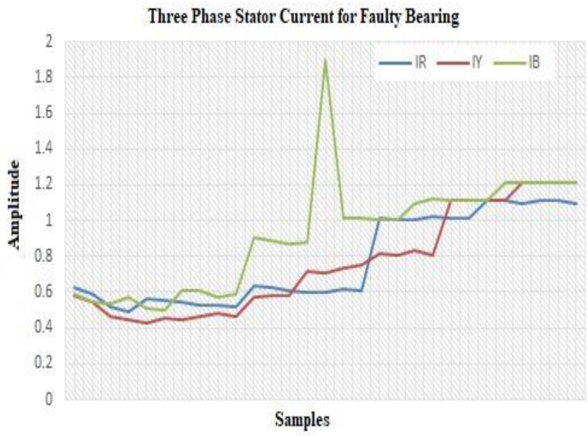

Fig.6. Three phase stator currents in faulty IM

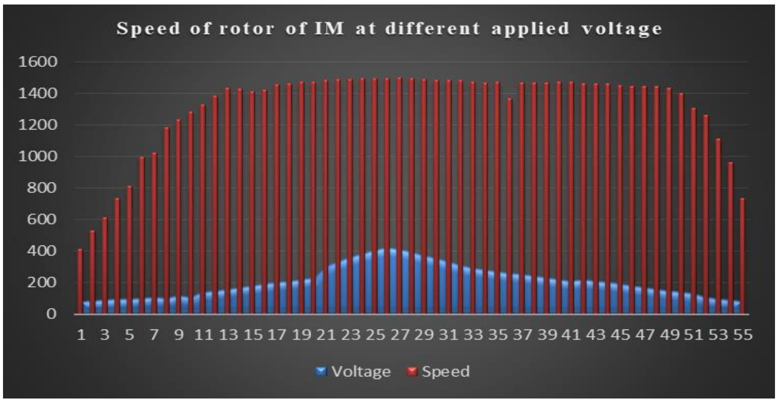

Fig.7. Applied voltage (blue) and shaft speed (red) of healthy induction motor

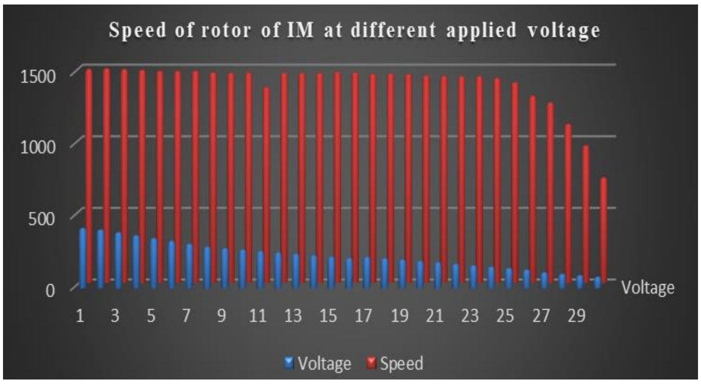

Fig.8. Applied voltage (blue) and shaft speed (red) of faulty induction motor

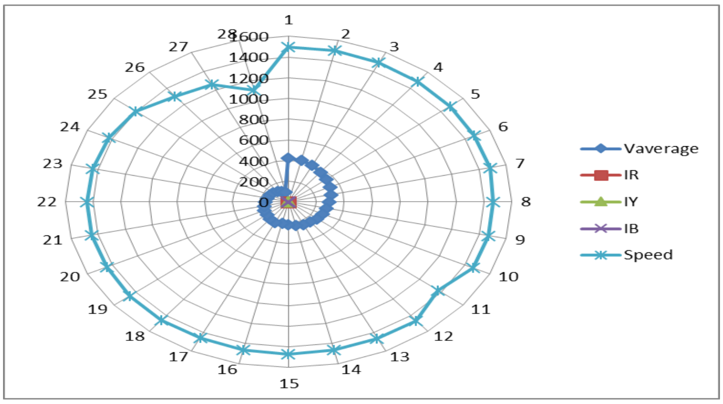

Fig.9. Radar chart of extracted features from experimental analysis for faulty IM

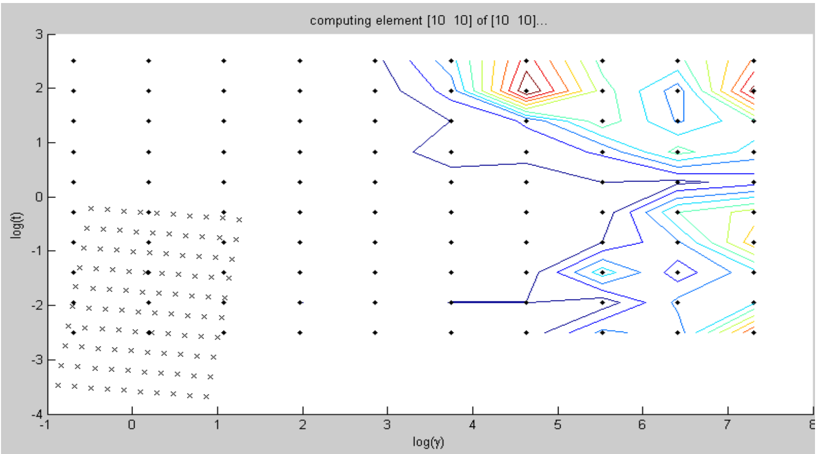

Fig.10. Mapping of data on hi-dimensional feature space using LS- SVM algorithm

Table 1. The training accuracy of LSSVM algorithm with kernel function polynomial and RBF

Data Type (Training Data Size, validation data size)	LSSVM with Polynomial Kernel		LSSVM with Gaussian RBF Kernel	
	(g, C)	ACC	ζ C	ACC
(210x5, 135x5)	(0.88, 102)	94.97	(0.1, 102)	97.14

VI. Conclusion

The primary component of an induction motor that supports the shaft to rotate rotor is the bearing. A bearing failure could cause the machine to completely shut down, hence results in mechanical as well as economic loss. In this manuscript, the LSSVM method has been successfully applied to identify bearings defects, especially lubrication loss and inner raceway defects. Although the success rate of the suggested method is 97.14% using Gaussian RBF kernel function, which is higher than SVM using polynomial kernel. Numerous more bearing-related flaws can be taken into account for the investigation using proposed method. The use of advanced feature parameters of LS-SVM and consideration of noise can enhance the efficacy of proposed method. The proposed method is simple and provides better result especially for medium size machines.

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