Misalignment Fault Prediction of Motor-Shaft Using Multiscale Entropy and Support Vector Machine

Alok Kumar Verma*, Somnath Sarangi, and Mahesh Kolekar

Abstract. Rotating machines constitutes the major portion of the industrial sector. In case of rotating machines, misalignment has been observed to be one of the most common faults which can be regarded as a cause for decrease in efficiency and can also for the failure at a time. Till date the researchers have dealt only with the vibration samples for misalignment fault detection, whereas in the present work both stator current samples and vibration samples has been used as a diagnostic media for fault detection. Multiscale entropy (MSE) based statistical approach for feature extraction and support vector machine (SVM) classification makes the proposed algorithm more robust. Thus, any non-linear behavior in the diagnostic media is easily handled. The proposed work has depicted an approach to analyze features that distinguishes the vibration as well as current samples of a normal induction motor from that of a misaligned one. The result shows that the proposed novel approach is very effective to predict the misalignment fault for the induction motor.

Keywords: Misalignment, Wavelet denoising, Multiscale entropy, Support vector machine, Fault diagnosis.

1 Introduction

Till date, online condition monitoring and fault detection of rotating machinery technique have been of great significant attentions among researchers. Recently it

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has observed that misalignment of motor shaft is one of the most important and easily encountered faults in the vast majority of rotating machinery. Misalignment condition in rotating machine is a condition where the centerlines of coupled shafts do not coincide with each other [1]. Loads increases due to misalignment on bearings and couplings. This increased load may lead to decrease in motor efficiency or damage of machine. Major factors that give rise to this respective misalignment conditions are asymmetry in applied loads, unequal settlement of foundation, improper assembly of machines etc, hence called the keys of misalignment [1, 2]. Thus good knowledge about the rotor shaft vibration and motor current signature analysis can be considered as the key elements for diagnosis and analysis of the misalignment in the rotating machines.

The non-linear behaviors encountered in mechanical system due to loading condition or damping, vibration in the friction, may change the normal vibration and current signals to the complex and non-linear [3]. It has been observed that commonly used signal processing techniques including time and frequency domain techniques as well as advanced signal processing techniques, like wavelet transform and time-frequency domain may all have limitations. [3]. Therefore, it resulted for need of techniques for non-linear dynamic parameter estimation which could provide a good alternative to extract the defect-related features hidden in the complex as well as non-linear vibration and current samples [3, 4]. An experiment [4] has been already done on non-linear dynamic parameters used for feature extraction and fault diagnosis and approximate entropy (ApEn). Approximate entropy was well illustrated and was selected as a working tool for rolling bearing fault detection. ApEn had also found its ways in the fields of physiological signal as well as vibration signal processing of rotating machine [3, 4], However ApEn reported more similarity in the time series and self-matching property of ApEn makes it to be heavily dependent on the length of time series [5].To overcome the limitations of ApEn, Richman and Moorman [6] introduced a new kind of entropy technique called sample entropy (SampEn) which has gained a lot of attention which excludes self-matching property [6, 7].

In this recent paper [8], a new entropy measure known as multi-scale entropy (MSE) has been introduced .The traditional entropy measure was measuring entropy on the single scale; there was no correspondence between the regularity and the complexity of the time-series. The researchers used this newly developed MSE technique to distinguish between young healthy hearts and congestive heart failure of a person. Considering a rotating machine as a combination of bearings, shafts and other mechanical components [9] and having a sufficient numbers of machine complexity that implies non-linear dynamic parameters applied on single scale (ApEn and SampEn of original time series) may be insufficient for characterizing machine vibration signals. Due to this reason, the multi-scale method was introduced and tried in the presented study with the idea of improving performances of machine fault diagnosis. With the best effort from author's literature survey in the field of fault diagnosis, very few work was done in which MSE has been applied and that was only with vibration signals. Long Zhang et al. [10] discussed about multi-scale entropy (MSE), taking into account multiple time scales, was introduced for feature extraction from fault of vibration signal. MSE with the support of vector machines constitutes the proposed intelligent fault diagnosis method. Jun-Lin Lin et al. [11] deals an approach to discover methods that distinguish the vibration signals of aligned motor from those of a misaligned one. Experimental results shows that classifiers based on these features obtain better and more accurate rates than those based on frequency-related features. Verma et al. [12] used MSE and grey-fuzzy algorithm to predict stator winding fault. They used MSE as a feature to deal with the nonlinearity exists in the stator winding vibration. Long Zhang et al. [13] introduced a bearing fault diagnosis method based on MSE and adaptive neuro-fuzzy inference system (ANFIS), in order to tackle the nonlinearity existing in bearing vibration as well as the uncertainty inherent in the diagnostic information.

Therefore, in this work authors investigate the misalignment fault by using diagnostic media like stator current as well as rotor vibration with the MSE, and that will be a novel approach, in order to tackle the nonlinearity existing in misalignment vibration and current. Presented work intuitively, a motor in a rotating machine is analogous to a heart in a person. This analogy motivates the use of MSE on vibration and current signals of motor in the presented work. Presented work proposes a method for detecting motor shaft misalignment by measuring the rotor vibration as well as stator current of an induction motor. Experimental result shows that the proposed algorithm can be used to classify effectively between aligned and misaligned motors using both rotor vibration as well as stator current of an induction motor.

2 Experimental Analysis

2.1 Experimental Setup

The entire experimental setup is shown in fig. 1 which comprises of four major sub-systems. It constitutes a three phase induction motor (Marathon Electric, 0.75HP) along with its accessories, constituting a data acquisition system, various sensors and a computer storage and a display, as shown in fig. 1. The induction motor with a wiring enclosure are adjoined on the left side of the system arrangement and that wiring enclosure of the motor support permits access to the 3-phase power supply and motor supply leads. The wiring enclosure attached with current probe is shown in Fig. 1 (b)

The roller bearings acts as the support factor to the rotor shaft of the given induction motor. The length of the shaft between two roller bearings is 0.72390 metre and the shaft diameter is of 0.0127 metre. Triaxial industrial accelerometer and current probe are two important sensors of this experiment. To collect vibration signals, an accelerometer was set up above the roller bearing on the right hand side which is shown in fig. 1 (d). Precision laser alignment kit has been used

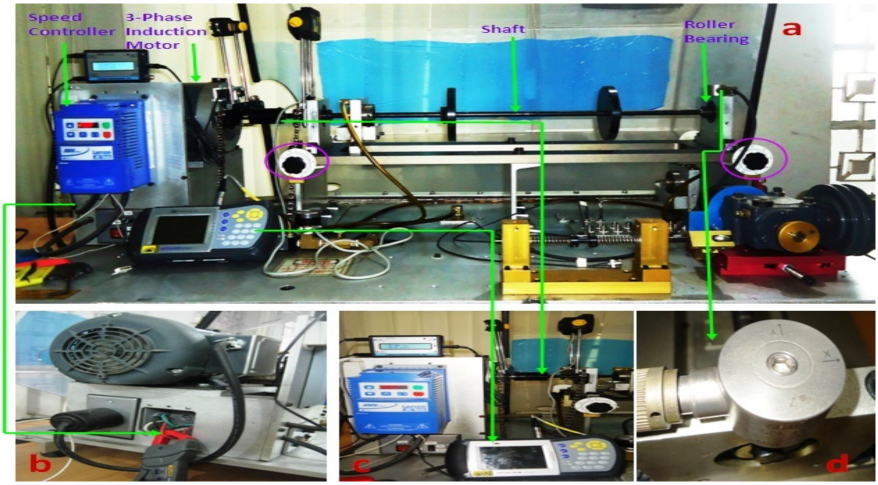

Fig. 1 Experimental set-up used: (a) Full view of the system arrangement, (b) Current probe, (c) Precision laser alignment kit and flexible coupling, (d) Triaxial industrial accelerometer with roller bearing

for investigating the alignment of shaft. The respective instrument constitutes one transmitter, a receiver and a controlling section as shown in fig. 1 (e). The complete specification of all the components used is mentioned in the following Table 1.

Table 1 Specifications of the components used in experimental setup

Sensors/ Machine	Manufacturer	Model/Serial No.	Sensitivity/ Specification
Accelerometer	IMI Sensors	604B31	Sensitivity=10.2 mV/(m/s2)
Current Probe	Fluke	I200s	100 mV/A
Laser Alignment Kit	Optalign smart	ALI 12.200	-------------
Induction motor	Marathon Electric	HVN 56T334F53033	0.75 HP, 50 Hz, 2850 RPM

2.2 *Experimental Details*

The present work enunciates the entire experimental procedure to differentiate the misaligned motor from that of the properly aligned one. The experimental setup along with its accessories in the aligned position is shown in fig 2. The misalignment condition is generated in the same setup by moving the base plate leftwards on horizontal plane which resulted in the movement of the support structure of the base plate as shown in fig 3 (with solid line). The corresponding schematics for the aligned and misaligned condition are illustrated using fig. 2 (a) and 2 (b). As shown in fig. 2 (b), a misalignment of 30 mils or 0.03 inches or 0.000762 meters between the driving and the driven shaft is provided to achieve the misalignment condition.

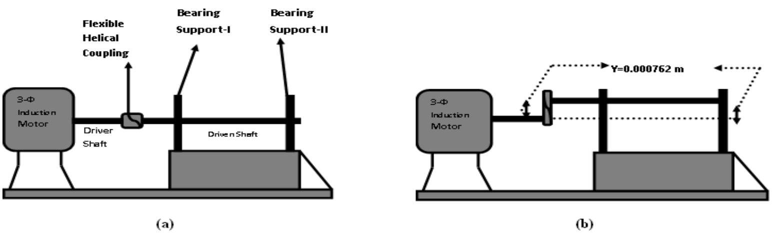

Fig. 2 (a) Aligned Setup, (b) Experimental Setup with misalignment of 0.000762 metre

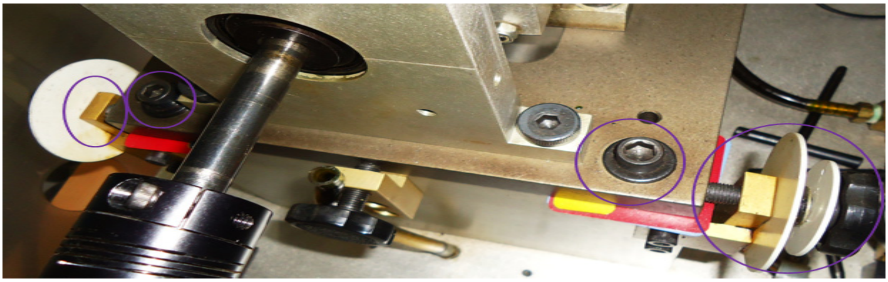

Fig. 3 Misalignment generation by moving support structure

Collectively, four sets of vibration as well as current signals were collected through this experiment. The first set of aligned vibration and current data (denoted by A_1) was collected maintaining the motor running at aligned condition. The motor was then misaligned with 0.000762 metre (on both side) by the process described above, and then the second set which is a misaligned data (denoted by M_1) was collected. Later the motor was adjusted back to its form of aligned condition, and the third set of aligned data (denoted by A_2) was obtained and stored. Lastly, the fourth set of data (denoted by M_2) was procured by misaligning the motor with 0.000762 meters (on both sides as process described above). Each set of data contained 26 records, recording the vibration and current signals at 26 different speeds ranging from 760 rpm to 1510 rpm with an increment of 30 rpm. Each record was a time series and containing 15364 signal values. The vibrational signals were obtained using the accelerometer and the current signals were collected by current probe at 5.12 s/s. Parameters used and their levels are shown in Table 2.

Table 2 Factors and levels considered for experiments

	Control Factor	**Level**
A	Rotational Speed (rpm)	760 to 1510
B	Alignment Cond. (mils)	0 & 2×0.000762 m

3 Proposed Method

The methodology used in the present investigation consists of four steps. The vibration and the current samples obtained from experiments are analyzed using Multiscale entropy (MSE). Further, the results of the MSE are denoised using wavelet transform. Support vector machine was used to classify the denoised MSE of vibration and current signals. Based on denoised MSE, support vector machine is employed to model the entire system and to give the performance. The result obtained from the above analysis is validated by performing the confirmation experiments. The step by step details of the analysis is mentioned in the sub sections 3.1 and 3.2.

3.1 Multiscale Entropy

It is the most prominent task to find out the regularity in a time series for both classifying and predicting future values in a time series. In 1991, Pincus [5], proposed a statistical measure for noisy time series, called approximate entropy (ApEn), to quantify the regularity of time series. In this proposed work, the MSE algorithm is used which is based on the SampEn for different scales of the same process instead of previously used regularity measure ApEn statistics. SampEn is used as replacement of ApEn and it measures the regularity in serial data. It measures the two sequences of m consecutive data within a tolerance r remain similar when one consecutive point is included.

ApEn (m, r, n) may be calculated for the time series of length N, according to the equation

$$\text{ApEn (m, r, N)} = \frac{1}{N-m}\sum_{i=1}^{N-m}\left(-\ln\frac{n_i^{m+1}}{n_i^m}\right), \tag{1}$$

where, r is tolerance of time series, m is pattern length and n is number of matching (including self match). ApEn is reported with certain disadvantages, such as heavy dependence on the length of the time series, smaller values for the shorter time series and lack of consistent results for different values of m and r. To overcome the shortcomings of ApEn, sample entropy (SampEn) as a new kind of entropy, this excludes the disadvantages of ApEn. As a refinement of ApEn, SampEn is used and it measures the regularity in series data. The SampEn is defined as

$$\text{SampEn (m, r, N)} = -\ln\left(\frac{\sum_{i=1}^{N-m} n_i^{m+1}}{\sum_{i=1}^{N-m} n_i^m}\right). \tag{2}$$

The value of r is taken as 0.15 times the standard deviation and m is taken as 2 for present analysis to avoid distortion. Costa et al. [13] proposed an algorithm called MSE, which considers SampEn at multiscale. MSE has been already successful to analyze physiological signals. Consider a time series, {X1, . . . , XN}, which is a coarse-grained time series in MSE is given by

$$y_j^{(\tau)} = \frac{1}{\tau}\sum_{i=(j-1)\tau+1}^{j\tau} \mathrm{X_i} \tag{3}$$

Where τ is known as scale factor, and for $\tau = 1$, that coarse grained time series is the original series. It is find that as increases, the length of the coarse-grained time series decreases. SampEn of a white noise falls quickly as the scale factor rises as shown in fig. 4. However, the SampEn of a pink or noise remains approximately stable as the scale factor rises. Therefore, white noise is more regular than pink noise.

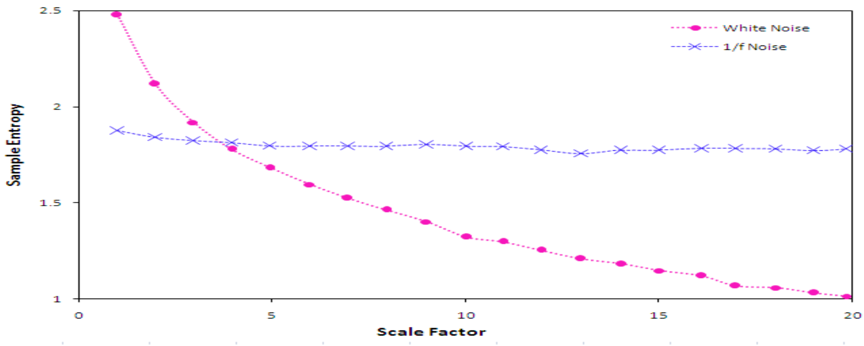

Fig. 4 Sample entropy with respect to the scale factor for coarse-grained time series of white and 1/f noises

Wavelet transform is one of the most effective and preferred method of denoising signals, although the effect of wavelet denoising depends on the signal types. Sample Entropy at different scale factor of normal and misaligned motors at 1100 rpm before and after denoising for vibration and current signals are enunciated using Fig. 5 and 6 respectively. It can be observed through fig. 5, that there exists increment of SampEn when the scale factor is small and reduction in SampEn when the scale factor is large. Similarly, the nature of periodicity of the current signals can also be observed from fig. 6. Thus, the information or the distinguishable characteristic present in both vibration and current signals are extracted or inferred from its respective sample entropies and can be consequently deployed to distinguish misaligned motors from that of the healthy ones.

Diagnosis or detection of motor shaft misalignment is carried out based on the vibration and current signals. The sample entropy of de-noised vibration and current signals is calculated for a scale factor ranging from 1 to 20. These calculated values are used as input to a SVM based classification algorithm to detect misaligned fault. Based on MSE the performance of the classifiers is discussed in result section, the denoising process is carried out using wavelet transform for both current and vibration samples. Daubechies wavelet transform was chosen for both vibration and current, which was implemented using Matlab and the parameter settings used for vibration samples are (tptr = ‘‘rigrsure”; n = ‘‘2”; wav = ‘‘db4”) and for the current samples, the parameter settings were (tptr = ‘‘rigrsure”; n = ‘‘6”; wav = ‘‘db2”).

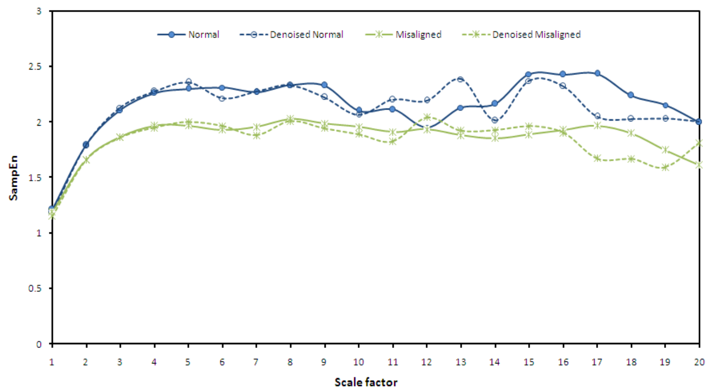

Fig. 5 Sample Entropy at different Scale factor of normal and misaligned motors at 1100 rpm before and after denoising for vibration signals

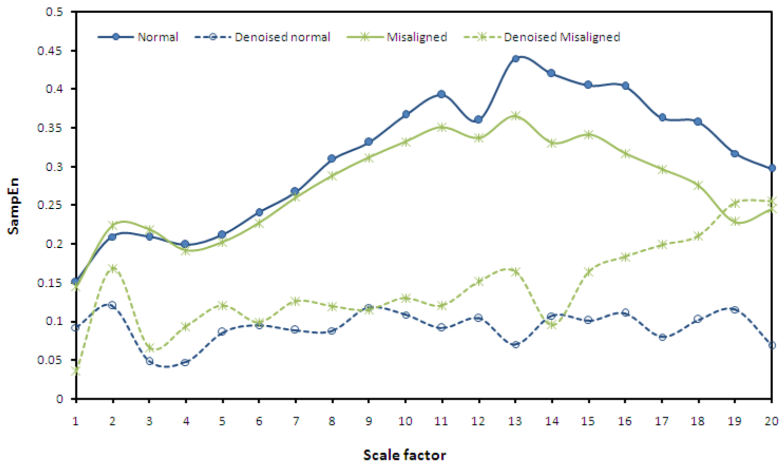

Fig. 6 Sample Entropy at different Scale factor of normal and misaligned motors at 1100 rpm before and after denoising for current signals

3.2 Support Vector Machines

The denoised MSE were used as input to the support vector machines (SVM) for detection of misalignment fault. SVM are relatively new method used for binary classification. The present work also requires a binary classification of the given samples to distinguish a healthy motor from that of a misaligned one. The basic idea is to find a hyperplane which separates the n-dimensional data perfectly into its two classes. First the input vectors are mapped into feature space (possible with higher dimension), either linearly or non-linearly, which is relevant with the selection of the kernel function. Then within the feature space, a hyperplane is constructed which separated the two classes (this can be extended to multiclass). As shown in fig. 7, the two hyperplanes are constructed on each side of the hyperplane that separates the data. The two classes are then separated by an optimum hyperplane, minimizing the distance between closest misaligned class points (+1 class) and properly aligned data points (-1 class), which are known as support vectors. The right side of the separating hyperplane represents the +1 class and the left-hand side represents the -1 class.

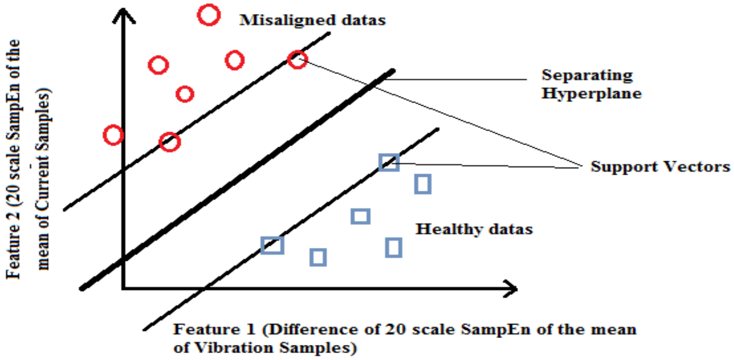

Fig. 7 SVM for misaligned and properly aligned motor classification

4 Results and Discussions

MSE technique is the only underlying basis of the present method of distinguishing or classifying the misaligned motors from that of healthy ones. The respective statistical based approach (MSE) easily tackles any existing non-linear behavior in the misalignment vibration or current samples, thus describing the regularity in the diagnostic information The allocated method examines the features that distinguishes the rotor vibration as well as stator current samples of aligned induction motor from that of a misaligned one with the help of an SVM

Table 3 Prediction accuracy on the training set for Test-1 and 2 of vibration and current (i.e., Test-1 = A_1 and M_1, Test-2 = A_2 U M_2 , total 52 samples, training set= 26 samples and testing set= 26 samples

Test	Media	Training Data	Cross Validation Accuracy (%)
1	Vibration	26	91.8%
2	Vibration	26	94.4%
1	Current	26	92.1%
2	Current	26	90.11%

Table 4 Prediction accuracy on the testing set for Test 1 and of vibration and current (i.e., Test-1 = A_1 and M_1, Test-2 = A_2 U M_2, total 52 samples, training set= 26 samples and testing set= 26 samples

Test	Media	Testing Data	Accuracy (%)	Time(Sec.)
1	Vibration	26	90.68%	2
2	Vibration	26	94.1%	2
1	Current	26	92.18%	2
2	Current	26	91.1%	2

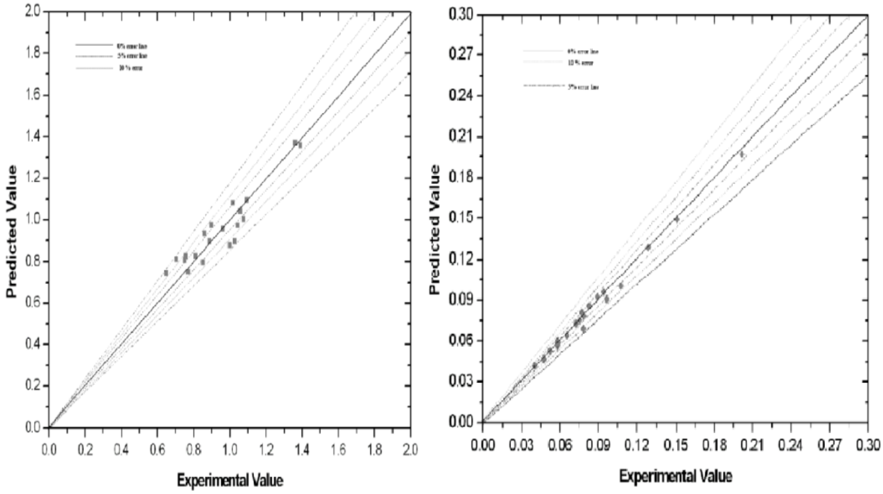

Fig. 8 Variation of predicted value with experimental value used for vibration and current of test-1

classifier. Test 1 was performed for both vibration and current samples used the sets A_1 and M_1, having 26 samples each. From the total of 52 numbers of samples, 26 samples were is randomly chosen as training set data and the remaining 26 samples were chosen as testing data set. Test 2 was used the sets A_2 and M_2, having 26 samples each and total 52 samples. As Test 1 26 samples were chosen as training set and the remaining 26 samples were chosen as testing data. Further, the SVM based classification was carried out using the following data: (a) stator current samples and (b) Rotor vibration samples. In this presented work, the number of input to the classifier is two (speed and normal or fault) and output is one (fault detection using vibration or current). In case of test-1, gives the maximum accuracy and is considered best for all three tests. The above classifier was then trained and tested for various values. The optimal value for the fault detection using vibration is shown in Table 3 and 4 and fig 8 shows the Variation of predicted value with experimental value used for vibration and current of test-1.

5 Conclusions

The main aim of the proposed approach was to investigate the robustness and effectiveness of distinguishing capability of the algorithm. The results infer that the misaligned motors can be easily distinguished from that of the healthy ones using stator current and rotor vibrational signals as the diagnostic media that were not done before. The developed system will lead to alter the long winded task of modeling and analysis of the vibration and current during misalignment fault with the help of MSE based statistical approach. From the given results, it can be observed that the best vibration accuracy is 94.68% and best current accuracy is 92.18% for all cases of the experimental values. The Present study clearly shows that the SVM model can be trained to predict the misalignment fault using vibration and current with reasonable accuracy. This approach can be used to detect different faults as well.

References

1. Piotrowski, J.: Shaft alignment handbook. CRC Press, New York (2006)
2. Verma, A.K., Sarangi, S., Kolekar, M.: Shaft Misalignment Detection using Stator Current Monitoring. International Journal of Advanced Computer Research 3, 305–309 (2013)
3. Yan, R.Q., Gao, R.X.: Approximate Entropy as a Diagnostic Tool for Machine Health Monitoring. Mechanical Systems and Signal Processing 21, 824–839 (2007)
4. Yan, R.Q., Gao, R.X.: Machine Health Diagnosis Based on Approximate Entropy. In: ICMT Instrumentation and Measurement Technology Conference, pp. 2054–2059. IEEE Press, Italy (2004)
5. Pincus, S.M.: Approximate entropy as a measure of system complexity. PNAS 88, 2297–2301 (1991)

6. Richman, J.S., Moorman, J.R.: Physiological Time-Series Analysis Using Approximate Entropy and Sample Entropy. Am. J. Physiol. H. 278, 2039–2049 (2000)
7. Haitham, M.A., Alan, V.S.: Use of Sample Entropy Approach to Study Heart Rate Variability in Obstructive Sleep Apnea Syndrome. IEEE Trans. Bio. Eng. 50, 1900–1904 (2007)
8. Costa, M., Goldberger, A.L., Peng, C.K.: Multiscale Entropy Analysis of Complex Physiologic Time Series. Phys. Res. Lett. 89, 68–102 (2002)
9. Fan, X.F., Zuo, M.J.: Machine Fault Feature Extraction Based on Intrinsic Mode Functions. Meas. Sci. Technol. 19, 245105, 12 (2008)
10. Zhang, L., Xiong, G., Liu, H., Zou, H., Guo, W.: An Intelligent Fault Diagnosis Method Based on Multiscale Entropy and SVMs. In: Yu, W., He, H., Zhang, N. (eds.) ISNN 2009, Part III. LNCS, vol. 5553, pp. 724–732. Springer, Heidelberg (2009)
11. Lin, J.L., Liu, J.Y., Li, C., Tsai, L., Chung, H.: Motor shaft misalignment detection using multiscale entropy with wavelet denoising. Expert Systems with Applications 37, 7200–7204 (2010)
12. Verma, A., Sarangi, S., Kolekar, M.: Stator winding fault prediction of induction motors using multiscale entropy and grey fuzzy optimization methods. Comput. Electr. Eng. (2014), `http://dx.doi.org/10.1016/j.compeleceng.2014.05.013`
13. Zhang, L., Xiong, G., Liu, H., Zou, H., Guo, W.: Bearing fault diagnosis using multiscale entropy and adaptive neuro-fuzzy inference. Expert Systems with Applications 37, 6077–6085 (2010)