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A Comprehensive Method for Detection of Induction Motors Bearing Faults

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A B S T R A C T

In this paper, some deficiencies of previously conducted studies are pointed out. These are including unreliability, dependent to motor and bearing specifications, lack of precision, drawbacks of experimental tests and etc. Here some important works will be reviewed. The proposed method which is based on wavelet decomposition and tracing the trend of statistical features variations, has overcame most of these deficiencies. Experimental results validated the proposed method. Finally, an approach to enhance detectability and precision in realistic industrial applications which is based on comparing power factor and temperature of tested and industrial application cases, will be presented.

Keywords: mechanical fault, single point defect (SD), distributed defect (DD), wavelet decomposition, trend of variation

1. Introduction

Multiple benefits of induction motors cause these motors to be the first choice of load-driving in industries[1]. From these, rational initial cost, lower maintenance in comparison to other electric motors, reasonable efficiency, technological maturity, ease of control and the most important one, capability of driving characteristically diversified loads are the most beneficial features of them [2].

Railway industry began with DC motors but nowadays they are focusing on induction motors (IMs), PMSM, BLDC and linear electric motors (LEMs). So referred to reasons considered, except for tansrapids which utilize LEMs, IMs are still the best choice[3]. Also It's evident that outbreak of faults and then failure of IMs leads to two basic difficulties: first case is heavy financial costs due to break in production or service and the second case which is really a high concern in railway industry is the customer trust on quality of service[4]. For example in urban transportation, consecutive stops lead to customer dissatisfaction so people's relish to utilize form industry decreases and restoration of this point of view will be too costly and also with future consequences. Nowadays IMs fault detection is an important matter which leads to significant industrial advantages. Production increasement, cost reduction and service improvement are included[5]. In this context, there have been lots of efforts which in an overview are categorized as theoretical and experimental works. Theoretical scrutiny of faults [5]–[11] can be compromising and helpful for future research but there has been a big concern for scholars that to what extent these results can be applicable. Experimental efforts [12]–[15] which are mainly based on those theoretical investigations may lead to effective results but still

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there is a great difference to what happens in reality so the same question arises. Generally IMs (which are drawing point of industries) faults fit into two classes of electrical and mechanical. Studies have shown that mechanical faults in rate of occurrence and imposed costs are leading. Multiple items have been studied as mechanical faults such as: bearing faults, eccentricity, misalignment, shaft curvature, imbalance distribution of shaft mass, elliptical shape of stator or rotor and etc. Undoubtedly bearing faults are the most prominent kind because according to reports about 50% of IMs out of services are due to bearing faults. To bear, two studies of IEEE and EPRI is considered as follows [16]

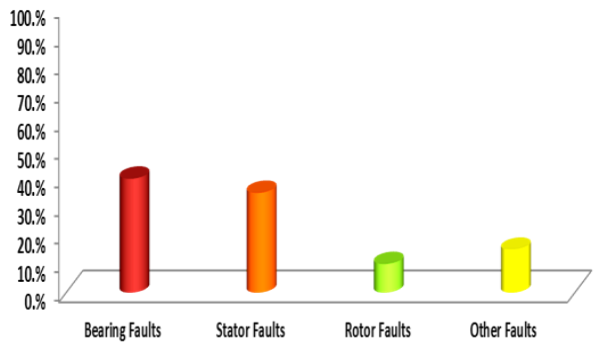

Figure 1. EPRI study on IM_s reliability

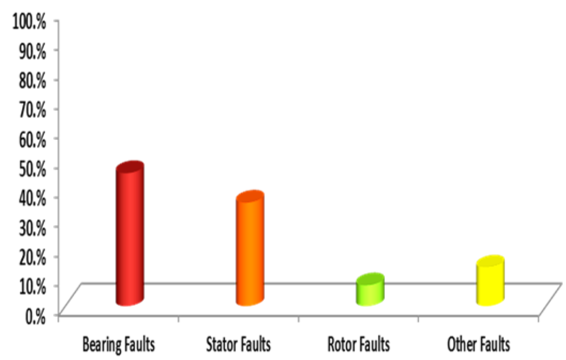

Figure 2. IEEE study on IM_s faults

To investigate mechanical faults, vibration is the most appropriate signal [17]. It is due to mounting vibration sensors on the nearest location to the fault (for example on bearing housing) so there will be certainly less noise and higher precision. Moreover due to the mechanical nature of these faults vibration assessment may lead to better results. The only signal which is somewhat a competitive alternative is current signal. Lots of studies [12], [18] have utilized it for fault detection. Basically in electrical motors, current signal variations are due to variation of airgap length, so studies have utilized current signal, are exposed to some reviews. We sense these variations from machine terminals so, there will be much noise injected into the signal. If we want to investigate mechanical faults by checking machine inductances, we must use Hall sensors but firstly, it is not possible to pose Hall sensors in all electrical machines and second because we need high precision sensors to distinguish small faults so the costs will be notable. Moreover machine inductances are under the influence of multiple factors such as: power supply incoming harmonics, rotor skewness, slot effects, saturation and etc [19], [20]. And these factors sensivity may also be variable in different conditions. Another important point here is that, in all machines there are two bearings: front bearing and end bearing. Since distinguishing of faults of these two bearings through the current signal is almost impossible thus in the case of detected faults, both bearings must be replaced and if fault detection system has made a mistake in its mission, there will be a catastrophic disorder. Also with vibration signal if we want to have a reliable diagnosis, we must place vibration sensors on housings of both front and end bearings [21]. It is worthwhile to note that, cost of vibration sensors in comparison to Hall sensors is much lower and moreover the application of them is more feasible. However, the cost of installing a fault detection system even with vibration sensors is not much low so it is recommended to use these systems limited to industries in which, production or service is critical and cease of production or service causes severe loss [4].

A comprehensive study of machine faults conducted in [16]. Although scholars were concerning about electrical machines failure lots of years ago, but they become more decided to take some actions in two past decades. Since there are lots of important studies on this subject, we cannot bring them all. So we just point out some effective and important works with a general sight. The initiation of new era on IMs mechanical fault detection was started by Toliyat [5] which was basically about evaluation of eccentricity on IMs. After that, Dorrel and Thomson [22] continued this study and depicted relations between airgap eccentricity and flux, current and vibration signals. Bangura and Demerdash [23] investigated similarities and differences between broken bar and eccentricity faults. Nandi [24] searched detection of rotor slots and other eccentricity related harmonics in different IMs. Bangura [8] used time series data mining and time stepping coupled FE to diagnose eccentricities and bar/end ring connector breakages. Wu [25] tried to eliminate effect of load oscillation on eccentricity detection. Xiaodong [26] considered effect of inclined eccentricity (misalignment) on performance of IMs. Discrete wavelet transform was utilized by Riera-Gausp [27] for transient detection of slip dependent fault components. Faiz [28] studied eccentricity faults comprehensively by means of FE. Nandi [29] proposed a method for detecting eccentricity based on nameplate parameters. Esfahani [30] investigated eccentricity and bearing faults by a multi sensor wireless system. And Gyftakis [31] suggested a novel and effective method of static eccentricity diagnosis in PSH IMs. All the mentioned studies were suffering from lack of precision in IMs modelling such that they were neglecting some important effects such as slot effects, rotor skewness, and saturable teeth reluctances. These factors affects directly on evaluation of inductances which are one of the most compromising methods of mechanical fault detection in IMs. Moreover, their methods of simulation were too time consuming. So Ganji [32] offered a broadband excitation technique for identification of IMs dynamic and static inductances. But it wasn't able to satisfy need for a precise model. In [33] Faiz evaluated inductances of IM under mixed eccentric conditions. Akbari [34] proposed a modified model of squirrel cage IM under general rotor misalignment fault. Lately, Ojaghi [35] introduced a comprehensive study on modelling eccentric squirrel cage IMs with slotting effect and saturable teeth reluctances. He also calculated relating inductances. However all aforementioned papers are related to eccentricities which show themselves in current signal in the form of:

$$f = [f_s \pm K f_r] \qquad \text{K=1, 2, 3...} \qquad (1)$$

In which f_s stands for supply frequency and f_r stands for rotor frequency and K is a positive integer. Bearing fault characteristic frequencies present in the frequency spectrum of current signal in the form of [19]:

$$f = [f_s \pm K f_c] \qquad \text{K=1, 2, 3...} \qquad (2)$$

f_c is one of the fault related frequencies in vibration signal. With a little care, we find these two cases become equal in certain frequencies [36] so finding a method, capable of detecting both cases by means of utilizing aforementioned equal frequencies could be a challenging study and leads to lower cost and time spending[4].

In case of bearing fault, numerous papers are presented so we go down to say just categorized form of articles without pointing out authors names: 1. some studies investigated theoretical models of bearing faults[9], [11], [37]. 2. Acquiring which signal is an important issue. In [38], [39] vibration signal, in [12], [18], [40] current signal and in [41], [42] acoustic signal is used. Also one can find comprehensive comparison between current and vibration signals in [17] and between vibration and acoustic signals in [43]. Characteristics of current signal such as: ease of access, cost effectiveness and etc. makes it an appropriate signal but it is noteworthy to say that in case of mechanical faults, vibration signal is the most sensitive signal so it is a preferable choice. 3. Ref [10] considered different types of bearing faults. They are single point (SD) and distributed defects (DD). Lots of authors tried to detect single point defects [44]–[46] and a few put afford into detection of distributed ones [47], [48] and some investigated both cases together [47]. 4. An introduction for bearing vibration signal processing presented in [49]. It is a useful guide for newcomers of this context. 5. One can see effect of machine speed on bearing fault detection in [50]. Park vector which is a reliable tool to diagnose bearing faults, presented in [47]. Authors considered both kinds of bearing faults, but a big concern here is that, in a noisy environment and different load conditions whether this method is still powerful? Furthermore this is a simple and really effective method even in early detection of faults but need for collecting three phase stator currents continuously cannot be completely desirable. 6. Statistical features are good candidates for tracing faults [13], [15], [51]–[54]. But attention must be paid that results for different load or speed conditions are not much acceptable. 7. Surely we can say that in case of having much data and the situation in which decision making is not easy, intelligent tools [21], [30], [55]–[58] are great alternatives. But they are complex systems and error of these methods are not considered at all, neglecting this point, they are really promising. 8. As all we know, industrial environments are so noisy so an effective method specially for finding single point fault features is noise cancellation [44], [59], [60]. However this method cannot be used effectively in case of distributed defects. Moreover the least amount of error in specifying filter bands may lead to loss of fault information or in some cases increase in noise amplitude. 9. Instantaneous energy spectrum [61] is another proposed method which in noisy condition shows unreliable results. 10. Ref [62] used instantaneous power factor as a tool for identifying faults but application of this method on distributed faults identification is not evaluated. 11. Motor efficiency [63] was used as an indicator to diagnose distributed faults but validity and precision of obtained results due to severe sensivity of efficiency to performance condition is under question. 12. Combining statistical time features and neural network conducted by [45] are also prone to some reviews that mentioned earlier. 13. Among the transformations in which, goal is exploitation from frequency, time-frequency or time domain information, wavelet has an exceptional position [52], [64], [65]. It is because of various features provided by it. One can perform transformation, filteration and noise reduction. But there are still some deficiencies such as: mother wavelet function, optimized level of decomposition, spectrum leakage and expansion and etc. 14. Morphological operators [65], [66] are helping us to reform shape of a signal. This method can be compromising for future signal processing because if morphological operators come into use as mother wavelet function, leakage and expansion will be the least. 15. Data mining approach is also another effective method [48]. However studied case here is not satisfactory to evaluate proposed method. 16. Finally it is noteworthy to say that proposing a unique method for investigating important mechanical faults is a desired aim [30], [47] which leads to cost reduction and more rational results. A comprehensive review and bibliography on IMs fault detection can be found in [67], [68] respectively. Research history which has mentioned here is not complete but almost includes a general view for about two decades of research in this context.

Altogether, the proposed method here is utilizing from statistical features of segmented time domain signal which is demodulated by means of wavelet transform. Based on the fact that due to realistic defects (such as erosion, lack of lubrication or passing electric current through metallic element) broadband changes happen in signals, (current or vibration) as it is obvious in figure 3, seeking exact frequencies seems to fail in this situation[4]. Moreover even with single point defects, existence of much noise in industrial environments leads us to face a signal like figure 3 so analysing trend of variation in segmented high resolution signal helps us to have more reliable and accurate condition monitoring. Since we don’t add to or remove anything from the signal, it has its natural form, so reliable results are guaranteed.

Rest of this paper is organized as follows: In the next section, the subject, how bearing faults happen and outbreak will be considered. So this section generally evaluates previous studies about their point of view to the fault creation and experimental test rigs. Next, the same thing about signal processing methods, in the section signal processing, will be conducted. After that, the proposed method will be suggested. Then case study specifications will be explained. In the next section results and discussions will be brought. Then an approach for improvement of detection precision in industrial applications will be introduced. And finally, conclusions will come.

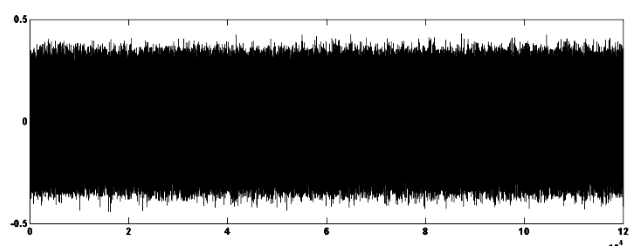

Figure 3. Captured vibration signal

2. How bearing faults happen and outbreak

In this section the aim is to peruse how bearing faults, as the most repetitive kind of mechanical faults, happen and outbreak. By the way, generally the overview of mechanical faults will not be ignored. In numerous studies bearing fault is considered as single point defect (SD) which in turn is due to outbreak of a local defect (or two or more) on bearing components surfaces and its (or their) impact as small amplitude periodic impulses on vibration or current signal. On the other hand, fault is considered as distributed defect (DD) with large extent, such as a long crack or general roughness of bearing component surfaces. As it comes from the name, impact of this class of faults on vibration or current signals causes widespread changes and not periodic impulses. SD and DD are obvious in figure 4 and 5 respectively.

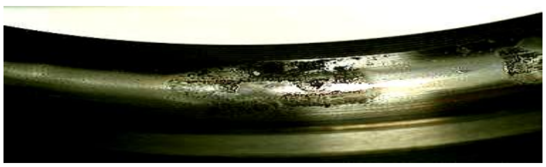

Figure 4. Single point defect

Figure 5. Distributed defect

It is said by experts that in reality, bearing faults emanate from microscopic cracks or bubbles below the bearing component surfaces. Existence of these defects due to production imperfectness is inevitable. Afterward, these defects penetrate gradually to the bearing surfaces due to loading or other causes such as overload, impact load, temperature increasement, etc. and show themselves in the form of SD or DD. If it is DD, as mentioned earlier leads to widespread changes in signal under investigation. But, suppose that defect outbreaks in the form of SD. However, all we know in industrial environments, specifically industries in which cease of production or service leads to severe loss (basic industries including steel, petrochemical and etc. and basic services including subway, etc.) are noise opulent. Generally, noise is distributed widespread and their relative amplitudes are higher than periodic impulses amplitudes due to single point defects. So it is expected to face with a signal having widespread circumstantial changes, something like DD signal which we know, even if it is escorted by noise, still has widespread changes in it. With another point of view, suppose that length of a defect is longer than the distance between the touch points of two adjacent balls (rollers). In this case, there is always at least one ball (roller), passing on the defected area, so the resulted signal may not be impulsive shape and may be close to the DD signal. This phenomenon can be compared with a situation in which a car is passing on a road which has many bumps, so there will be impulsive vibration. But if it is a dirt road, vibration will be much higher and close to the form of noise. Mentioned cases make us to categorize studies in three classes. First class are studies which have connivance sight to bearing faults and therefore analyze totally fictitious and impractical faults[4], [9], [51], [65]. They produced faults by perforating bearing components. It is noteworthy that removing and replacing, in turn may impose some defects, so precision and even validity of our results will be under question.

According to different industrial reports, the main reasons of bearing faults are improper lubrication, humidity and improper maintenance which are shown in figure. 6 obviously [69].

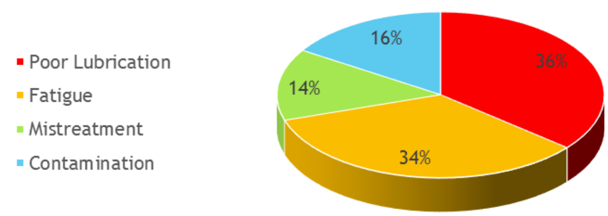

Figure 6. Industrial reports about reasons of bearing failure

However, other factors such as passing electrical current through the bearing, oil contamination and etc are also included. Generally, it is evident that such factors may lead outbreak of DD and it is so unlikely to have a hole in effect of improper lubrication or humidity. On the contrary, it is more realistic and probable to have general roughness due to inappropriate lubrication or corrosion. The second group have considered mentioned points to some extent and have produced both SD and DD, but there are still some reviews about the method they used to create the faults[39], [47], [54], [69]. In addition, the test bench they have used in some cases are far from reality. As an example in a study, authors have used an isolated synchronous generator to feed induction motor which is under test and have ignored incoming harmonics to the drive or in[42], [62], [70],[71] , they even have not used drive to feed electrical motor. In both cases we know that, injecting more harmonics could have increased motor vibration or torque oscillation which in turn leads to vibration enhancement. In some cases all the mechanical noise are neglected. They implement load changing by a dynamometer (DC generator) and a set of resistances to waste energy or in other efforts by a synchronous generator and a rectifier and a set of resistances to waste energy. And it is also implemented by a controlled coupling brake. However, certainly we know that mechanical tensions which are noise in our diagnosis process, may exist and surely affect on results obtained from vibration or current signals. Finally the third group[30],[45], [48] [72]who has observed aforementioned points to some extent and can go through the next stage which is signal processing. Although, one can improve resulting signals of first and second groups by adding noise but this may lead the experiments to be worthless.

3. Signal processing

The main objective is to have simple, low cost, precise, reliable and expandable diagnosis. It is safe to say that, after meeting the requirements of previous section, it is signal processing which has an important role in the way to attain this purpose. In recent years numerous methods have used by researchers which stand in three general groups. The first group are transforms such as: Fourier, wavelet, Hilbert, etc transform in which the aim is to utilize from frequency, time or time-frequency information of signal in accordance to what we have and what we want [14], [48], [52], [61], [65]. Challenges in these methods are: resolution, transform mother function, effect of transformation on data, stability and reliability of outputs, sensivity to noise, etc. Note that still this kind of signal processing, depending on application can be the best choice for fault detection.

The second group efforts are based on noise reduction of signal [59], [60], [72]. The goal here is to increase the signal to noise ratio. This method generally is exploited for diagnosing SDs, but in the case of DD, it is not much trustable. Even in case of single point defects due to difficulties to synchronize healthy (noise) and faulty (noise + desired signal) signals, existence of very little lagging may lead to increase noise amplitudes and unreliable results. It is more common in real industrial applications where fault frequency components and noise frequency components may be the same. However as mentioned earlier, DD symptoms are propagated throughout the signal, so removing some parts of signal (transformation to frequency domain and then filtering) leads to exclusion of fault indices and low precision decision making.

The third kind of applied methods are combinations of previously mentioned methods. Lately an important question has occupied researchers' mind [13] which is expandability of proposed methods. Whether we can apply a proposed method related to a specific case study to other different case studies? Or in other word is it possible to utilize from one fault detection method for a wide range of power and specifications of an understudy machines? Another important question which has to be answered is do they evaluate errors of fault detection methods? And if a complicated method goes wrong is it possible to troubleshoot it easily? Moreover, these systems often cost so much, whether unit cost of these fault detection methods are reasonable and applicable?

4. Proposed method

The proposed method is simple, intelligent, reliable, inexpensive and feasible in industrial applications. As mentioned earlier, transforms are often the most effective signal processing tools. Among them, wavelet has a specific position because it is a bipositional signal processing tool which gives us both time and frequency domain information. Actually the form of mother wavelet function we use, will have inevitable effects on results. But if we use time domain decomposed signal, we make as less as possible changes but splitting signal into smaller sections to enhance precision. Steps are as follows:

1. Choosing mother wavelet function: Here 2nd order dmyer mother wavelet is chosen for two reasons: firstly, correlation analysis between the original signal and combination of decomposed signal sections shows good agreement. Second, this wavelet is impulse shape which gradually

attenuates along both sides so it can be a comparable shape of SD frequency with its sidebands.

2. Number of decomposition levels: 10 level decomposition conducted. The goal is making smaller under investigation bands to enhance precision. Note that after tenth level, residual is going to be a straight line with no useful information about the fault.

3. Investigation of variation of statistical features: Finally, the trend of variation of statistical features throughout the 10 level decomposition has been studied. Comparing trends of healthy and faulty statistical features leads us to existence of fault. Among the statistical features such as: mean, median, standard deviation, crest factor, etc, we chose mean and standard deviation because they show the most tangible variation due to existence of fault. Note that, some features such as mean and median show the same behavior, so one of them is selected.

5. Case study specifications

Experiments, motor, bearing and fault specifications which are explained in this section, are all adopted from Case Western Reverse university bearing data center [73]. Data is gathered for healthy and faulty bearings. Data collection rate is 12000 point/second and rotor speed during each data acquisition is recorded to help us tracing fault frequencies. Experiments are conducted on a 2 HP IM. Bearing faults are created using electrical discharge machine (EDM). Faults are created on bearings three components and data collection is performed under 0 to 3 HP loads with corresponding 1797 to 1720 RPM speeds. Deep grove ball bearing SKF 6205-2RS JEM is used. For full information about bearing specifications and generally test rig visit [74].

Vibration data is gathered using accelerometers which are placed on the bearing's housings by their magnetic plates. Accelerometers are placed on 12 O'clock position at both fan and end bearings. Data is collected using a 16 channel DAT and preprocessed in MATLAB environment.

6. Results and discussion

Figures show that often we see the same trends but some little or big differences also exist. However, our reference is our case study. Comparing studied case trends to practical case one, if they are almost the same, your decision will be faulty case. Results for inner race fault are shown in figures 7.a, b, c and d for 0, 1, 2, 3HP loads respectively. It is obvious that mean feature can be a good indicator of existence of fault. With load increasement, detectability also increases because faulty and healthy cases become more separated.

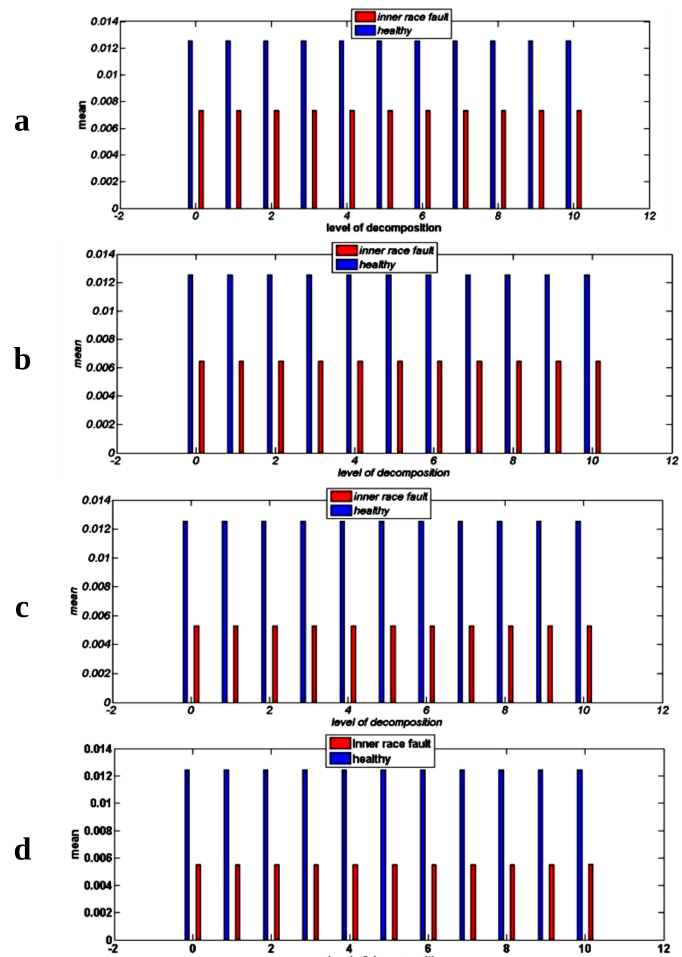

Figure 7. Mean feature for inner race fault: a) no load, b) 1HP, c) 2HP, d) 3HP

In case of standard deviations which are shown for inner race fault in figures 8.a b, c and d corresponding to 0, 1, 2, 3HP loads, results are different to some extent. For original signal, result has a different trend and this difference increases with loading such that for 3HP faulty and healthy cases have about 0.2 difference even though, it is about 0.02 for no load condition. On the other hand levels after 8th level, don't show obvious difference and these differences decrease with loading such that for 3HP, 7th level also become unreliable. So attention must be paid if we want to use this feature as a fault indicator. With load increasement, standard deviation become a more powerful feature for original signal although detectability of other levels decrease gradually. Another important point here is that we can define a threshold for mean features but it is not possible to define a constant threshold for standard deviation.

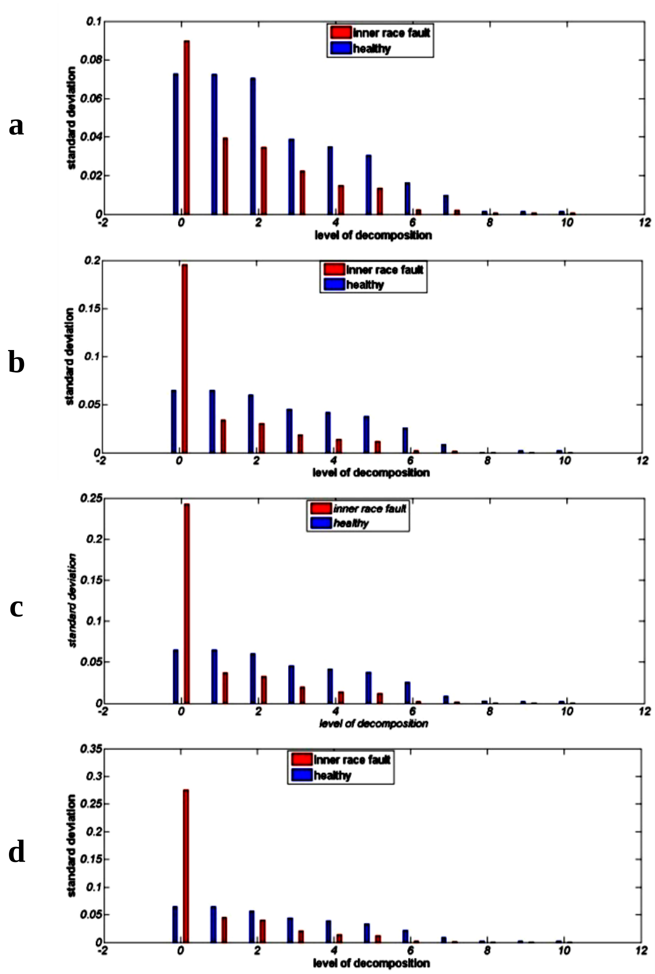

Figure 8. Standard deviation for inner race fault: a) no load, b) 1HP, c) 2HP, d) 3HP

Results for ball defect are shown in figures 9.a, b, c and d for mean and in figures 10.a, b, c and d for standard deviation according to 0, 1, 2 and 3HP loads respectively. Results are almost the same which is the most important point here. Our proposed method is independent of bearing fault type and responds significantly to any type of bearing faults. Moreover, it is independent of bearing or motor specifications so it can be a reliable and precise method.

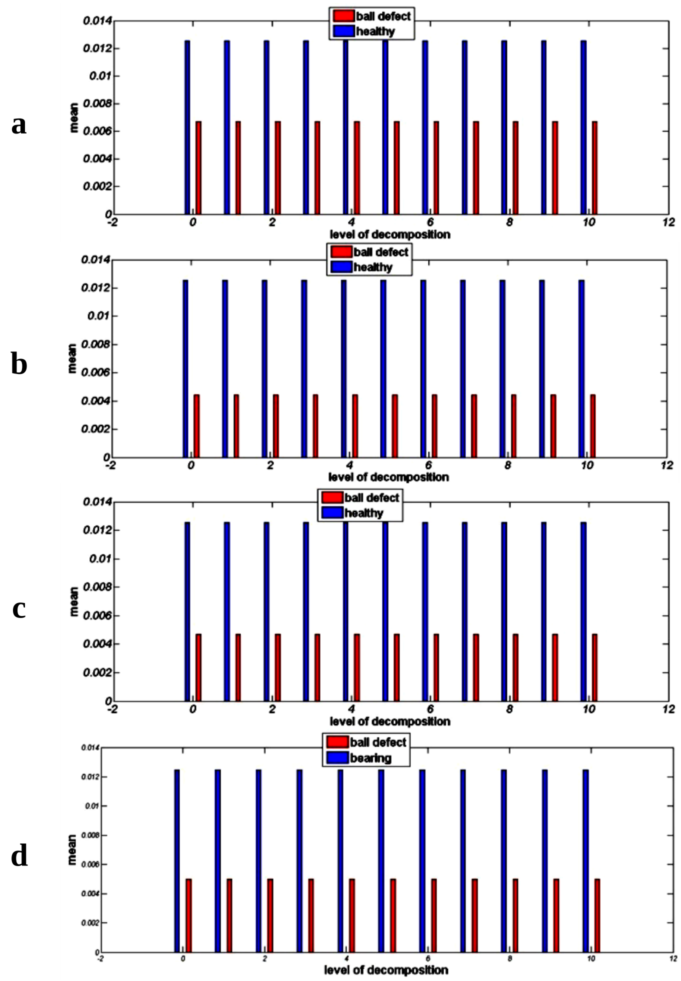

Figure 9. Mean feature for ball defect: a) no load, b) 1HP, c) 2HP, d) 3HP

However, choosing threshold, variation limits for both mean and standard deviation and importance factor which we specify to each decomposition stage, can be arranged according to the special case and desired precision we are looking for. For instance, one can choose variation band so small, as a result there is little inclusion possibility of practical data in the band or on the contrary, choosing wide band leads to increasement of wrongly detected faults so there will be lesser precision.

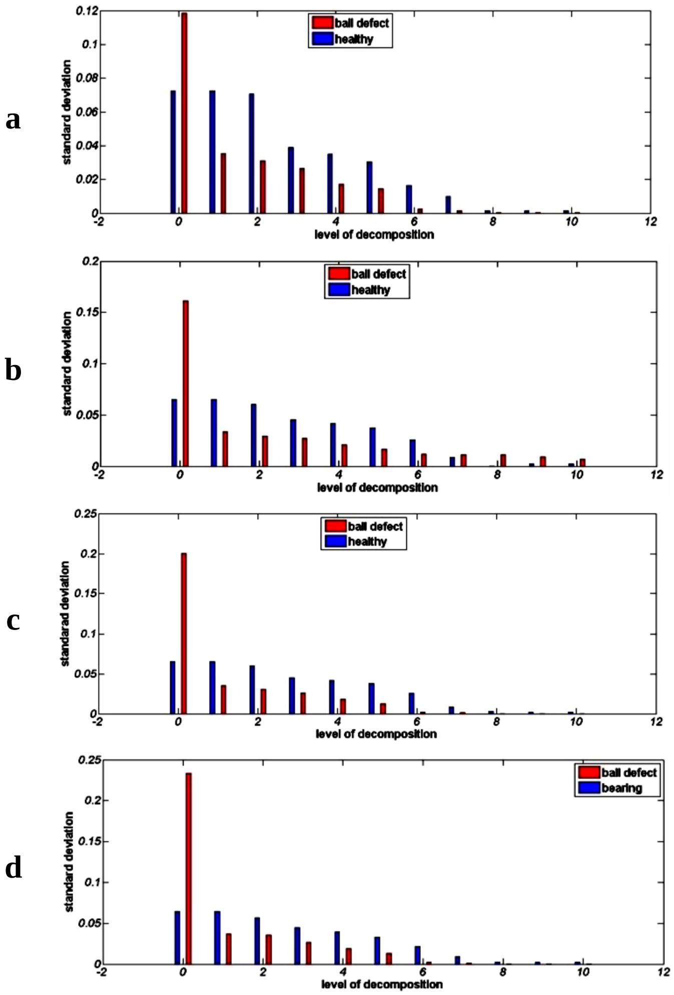

Figure 10. Standard deviation for ball defect: a) no load, b) 1HP, c) 2HP, d) 3HP

On the other hand, it is possible to limit comparisons to some worthy stages or even specify bigger importance factors to some fault information opulent stages. Here the same importance factors for all the stages are chosen.

7. Improvement of fault detection precision in practical industrial applications

Still there is a question about expandability of proposed method. Often, in specific industries, power range and specifications of operating electrical motors are almost the same. For example in railway industry, it is expected to see almost the same electrical motors in rolling stocks related to a specific line. So it is possible to utilize from experimental results related to a resemble motor and expand them to the other motors. But still there is a question which is how one can confirm experimental results to the practical cases?

For this purpose, suggestion is the following approach: by placing temperature sensor, one can get housing temperature. In addition, it is also required to record motor power factor during the test. After comparing to the industrial case, it is feasible to represent these three conclusions: 1. if comparing test decomposition stages to practical case, says there exists fault and observed temperature and power factor are also the same, so one can say that bearing fault has happened. 2. If the comparison of tested and practical cases shows faulty condition but, power factor and temperature are not the same and are far apart, we have two situations: a) Fault has happened but it is not the bearing fault. b) Bearing fault and another kind of fault(s) have happened simultaneously. 3. If there is no agreement between tested and practical results, no faults has happened. Appling this approach leads to detection precision increasement. However, it is evident that, if motor specifications change drastically, validity of this approach will be under question.

8. Conclusions

There are some deficiencies in conducted studies related to mechanical faults which are expressed here in detail. Among them, the most important one could be lack of a comprehensive method to investigate bearing faults. The proposed method is a comprehensive method to investigate bearing faults such that, it is independent of motor and bearing specifications and responds well to different kinds of bearing defects. Experimental results have been validating this claim. Vibration signal is decomposed into some segments, using wavelet, to enhance precision. Then statistical features including mean and standard deviation are utilized to show existence of fault. After that, a method for improvement of detection precision presented which is based on comparing power factor and temperature of tested and industrial application cases. It is suggested to use other mother wavelet functions such as morphological functions to increase future works detectability and reliability.

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References

[1] A. Hughes and B. Drury, Electric Motors and Drives (Fourth Edition) Fundamentals, Types and Applications. Elsevier Ltd, 2013.

[2] I. Motors, E. Use, and M. Basics, Induction Motor Testing and Evaluation, Spectrum, 440 (1996) 1–14.

[3] N. Hashemnia and B. Asaei, Comparative study of using different electric motors in the electric vehicles, 18th Int. Conf. Electr. Mach., no. c, 1–5, 2008.

[4] S. J. Hoseini, Fault Detection Methods Analysis in Bearings of Induction Motors : An Overview, (2015) 1–5.

[5] H. A. Toliyat, M. S. Arefeen, A. G. Parlos, and S. Member, A method for dynamic simulation of air-gap eccentricity in induction machines, 32 (4) (1996) 910–918.

[6] W. T. Thomson, S. M. Ieee, and A. Barbour, On-line current monitoring and application of a finite element method to predict the level of static airgap eccentricity in three-phase induction motors, 13 (4) (1998) 347-357.

[7] S. Nandi, R. M. Bharadwaj, H. A. Toliyat, and S. Member, Performance Analysis of a Three-Phase Induction Motor Under Mixed Eccentricity Condition, 17 (3) (2002) 392–399.

[8] J. F. Bangura, R. J. Povinelli, S. Member, N. A. O. Demerdash, and R. H. Brown, Diagnostics of Eccentricities and Bar / End-Ring Connector Breakages in Polyphase Induction Motors Through a Combination of Time-Series Data Mining and Time-Stepping Coupled FE – State-Space Techniques, 39 (4) (2003) 1005–1013.

[9] F. Immovilli, C. Bianchini, M. Cocconcelli, A. Bellini, and R. Rubini, Bearing Fault Model for Induction Motor With Externally Induced Vibration, 60 (8) (2013) 3408–3418.

[10] J. R. Stack, T. G. Habetler, and R. G. Harley, Fault Classification and Fault Signature Production for Rolling Element Bearings in Electric Machines, 40 (3) (2004) 735–739.

[11] M. Blödt, P. Granjon, B. Raison, and G. Rostaing, Models for Bearing Damage Detection in Induction Motors Using Stator Current Monitoring, 55 (4) (2008) 1813–1822.

[12] J. R. Stack, T. G. Habetler, and R. G. Harley, Bearing Fault Detection via Autoregressive Stator Current Modeling, 40 (3) (2004) 740–747.

[13] G. Georgoulas, T. Loutas, and C. D. Stylios, Bearing fault detection based on hybrid ensemble detector and empirical mode decomposition, Mech. Syst. Signal Process., 41 (1-2) (2013) 510–525.

[14] T. Doguer, J. Strackeljan, O. Magdeburg, and F. Maschinenbau, New Time Domain Method for the Detection of Roller Bearing Defects, (2008) 1–11.

[15] X. Jin, M. Zhao, T. W. S. Chow, S. Member, and M. Pecht, Motor Bearing Fault Diagnosis Using Trace Ratio Linear Discriminant Analysis, 61(5) (2014) 2441–2451.

[16] G. . Singh and S. Ahmed Saleh Al Kazzaz, Induction machine drive condition monitoring and diagnostic research—a survey, Electr. Power Syst. Res., 64 (2) (2003) 145–158.

[17] F. Immovilli, A. Bellini, R. Rubini, and C. Tassoni, Diagnosis of bearing faults in induction machines by vibration or current signals: A critical comparison, IEEE Trans. Ind. Appl., 46 (4) (2010) 1350–1359.

[18] M. E. H. Benbouzid, M. Vieira, and C. Theys, Induction motors' faults detection and localization using stator current advanced signal processing techniques, IEEE Trans. Power Electron., 14 (1) (1999) 14–22.

[19] G. Joksimovic, M. Djurovic, and J. Penman, Cage rotor MMF: Winding function approach, IEEE Power Eng. Rev., 21 (4) (2001) 64–66.

[20] S. Nandi, Modeling of induction machines including stator and rotor slot effects, IEEE Trans. Ind. Appl., 40 (4) (2004) 1058–1065.

[21] M. Liang and H. Faghidi, Intelligent bearing fault detection by enhanced energy operator, Expert Syst. Appl., (2014) 1–12.

[22] D. G. Dorrell, W. T. Thomson, S. Member, and S. Roach, Analysis of airgap flux, current, and vibration signals as a function of the combination of static and dynamic airgap eccentricity in 3-phase induction motors, 33 (1) (1997) 24–34.

[23] J. F. Bangura, S. Member, and N. A. Demerdash, Comparison Between Characterization and Diagnosis of Broken Bars / End-Ring Connectors and Airgap Eccentricities of Induction Motors in ASD ' s Using a Coupled Finite Element-State Space Method, 15 (1) (2000) 48–56.

[24] S. Nandi, S. Ahmed, S. Member, H. A. Toliyat, and S. Member, Detection of Rotor Slot and Other Eccentricity Related Harmonics in a Three Phase Induction Motor with Different Rotor Cages, 16 (3) (2001) 253–260.

[25] L. Wu, S. Member, X. Huang, T. G. Habetler, and R. G. Harley, Eliminating Load Oscillation Effects for Rotor Eccentricity Detection in Closed-Loop Drive-Connected Induction Motors, 22 (4) (2007) 1543–1551.

[26] X. Li, Q. Wu, and S. Nandi, Performance Analysis of a Three-Phase Induction Machine With Inclined Static Eccentricity, 43 (2) (2007) 531–541.

[27] J. A. Antonino-daviu, A General Approach for the Transient Detection of Slip-Dependent Fault Components Based on the Discrete Wavelet Transform, 55 (12) (2008) 4167–4180.

[28] J. Faiz, B. M. Ebrahimi, B. Akin, and H. A. Toliyat, Comprehensive Eccentricity Fault Diagnosis in Induction Motors Using Finite Element Method, 45 (3) (2009) 1764–1767.

[29] S. Nandi, S. Member, T. C. Ilamparithi, S. Member, S. Bin Lee, S. Member, D. Hyun, and S. Member, Detection of Eccentricity Faults in Induction Machines Based on Nameplate Parameters, 58 (5) (2011) 1673–1683.

[30] E. Esfahani, Multi-sensor Wireless System for Fault Detection in Induction Motors, p. 53, 2012.

[31] K. N. Gyftakis and J. C. Kappatou, A Novel and Effective Method of Static Eccentricity Diagnosis in Three-Phase PSH Induction Motors, 28 (2) (2013) 405–412.

[32] I. M. Dynamic, S. Inductance, I. Using, and B. E. Technique, Induction motor dynamic and static inductance identification using, Energy, 13 (1) (1998) 15–20.

[33] J. Faiz, I. T. Ardekanei, and a. T. Hamid, An evaluation of inductances of a squirrel-cage induction motor under mixed eccentric conditions, IEEE Trans. Energy Convers., 18 (2) (2003) 252–258.

[34] MODIFIED MODEL OF SQUIRREL CAGE INDUCTION, 54 (2013) 185–201.

[35] M. Ojaghi and S. Nasiri, Modeling Eccentric Squirrel-Cage Induction Motors With Slotting Effect and Saturable Teeth Reluctances, 29 (3) (2014) 619–627.

[36] I. Ozelgin, Analysis of magnetic flux density for airgap eccentricity and bearing faults, Int. J. Syst. Appl. Eng. Dev., 2 (4) (2009) 162–169.

[37] J. R. Stack, T. G. Habetler, and R. G. Harley, Fault Signature Modeling and Detection of Inner Race Bearing Faults, 2005.

[38] J. Liu, Detrended Fluctuation Analysis of Vibration Signals for Bearing Fault Detection, 0–4.

[39] J. Zarei, M. A. Tajeddini, and H. R. Karimi, Vibration analysis for bearing fault detection and classification using an intelligent filter, Mechatronics, 24 (2) (2014) 151–157.

[40] L. Eren and M. J. Devaney, Neural Network Based Motor Bearing Fault Detection, no. May, 2004.

[41] M. a a Elmaleeh and N. Saad, Acoustic emission techniques for early detection of bearing faults using LabVIEW, Proceeding 5th Int. Symp. Mechatronics its Appl. ISMA 2008.
[42] M. Amarnath, V. Sugumaran, and H. Kumar, Exploiting sound signals for fault diagnosis of bearings using decision tree, Measurement, 46 (3) (2013) 1250–1256.
[43] X. Liu, X. Wu, and C. Liu, A comparison of acoustic emission and vibration on bearing fault detection, Proc. Int. Conf. Transp. Mech. Electr. Eng. (2011) 922–926.
[44] Y. Zhang and M. Liang, Bandstop filtering for interference removal in bearing fault detection, 2012.
[45] M. D. Prieto, S. Member, G. Cirrincione, A. G. Espinosa, J. A. Ortega, H. Henao, and S. Member, Bearing Fault Detection by a Novel Condition-Monitoring Scheme Based on Statistical-Time Features and Neural Networks, 30 (8) (2013) 3398–3407.
[46] I. Y. Önel, K. B. Dalci, and İ. Senol, Detection of bearing defects in three-phase induction motors using Park's transform and radial basis function neural networks, Sadhana, 31 (3) (2006) 235–244.
[47] J. Zarei and J. Poshtan, An Advanced Park ' s Vectors Approach for Bearing Fault Detection includes, 2006.
[48] D. He, R. Li, and J. Zhu, Plastic bearing fault diagnosis based on a two-step data mining approach, Ind. Electron. IEEE Trans., 60 (8) (2013) 3429–3440.
[49] S. a. McInerny and Y. Dai, Basic vibration signal processing for bearing fault detection, IEEE Trans. Educ., 46 (1) (2003) 149–156.
[50] J. R. Stack, T. G. Habetler, and R. G. Harley, Effects of machine speed on the development and detection of rolling element bearing faults, IEEE Power Electron. Lett., 1 (1) (2003) 19–21.
[51] K. A. Loparo, A new bearing fault detection and diagnosis scheme based on hidden markov modeling of vibration signals, 1–4.
[52] P. Li, Bearing Fault Detection via Wavelet Packet Transform and Rough Set Theory, 601 (114) (2004) 1663–1666.
[53] T. Boutros and M. Liang, Detection and diagnosis of bearing and cutting tool faults using hidden Markov models, Mech. Syst. Signal Process., 25 (6) (2011) 2102–2124.
[54] C. Park, Y. Choi, and Y. Kim, Early fault detection in automotive ball bearings using the minimum variance cepstrum, Mech. Syst. Signal Process., 38 (2) (2013) 534–548.
[55] J. Zarei, J. Poshtan, and M. Poshtan, Bearing fault detection in induction motor using pattern recognition techniques, IEEE 2nd Int. Power Energy Conf., 2 (7) (2008) 3258–3264.
[56] I. P. Engineering, O. Conference, and T. Jewel, Detection and Classification of Induction Motor Faults Using Motor Current Signature Analysis and Multilayer Perceptron, (2014) 35–40.
[57] B. Li, M. Y. Chow, Y. Tipsuwan, and J. C. Hung, Neural-network-based motor rolling bearing fault diagnosis, IEEE Trans. Ind. Electron., 47 (5) (2000) 1060–1069.
[58] K. Teotrakooll, M. J. Devaney, and L. Eren, Bearing Fault Detection in Adjustable Speed Drives via a Support Vector Machine with Feature Selection using a Genetic Algorithm, 2008.
[59] Y. Li, M. Ieee, T. Wang, and M. Ieee, Signal Segmentation for Isolating the Influence of PQ Variation and Machine Manufacturing Imperfections on Bearing Fault Detection, 2013.
[60] M. Torbatiao, M. H. Kahaei, and J. Poshtan, Bearing Fault Detection using Level-Dependent Noise Reduction Technique, 146–149.
[61] H. Li, Bearing Fault Detection Based on Instantaneous Energy Spectrum, Image Signal Process. (CISP), 2010 3rd Int. Congr., 7 (2010) 2594–2598.
[62] A. Ibrahim, M. El Badaoui, F. Guillet, and F. Bonnardot, A New Bearing Fault Detection Method in Induction Machines Based on Instantaneous Power Factor, IEEE Trans. Ind. Electron., 55 (12) (2008) 4252–4259.
[63] L. Frosini and E. Bassi, Stator current and motor efficiency as indicators for different types of bearing faults in induction motors, IEEE Trans. Ind. Electron., 57 (1) (2010) 244–251.
[64] J. Chebil, G. Noel, M. Mesbah, and M. Deriche, Wavelet Decomposition for the Detection and Diagnosis of Faults in Rolling Element Bearings, 3 (4) (2009) 260–267.
[65] B. Li, P. L. Zhang, Z. J. Wang, S. S. Mi, and D. S. Liu, A weighted multi-scale morphological gradient filter for rolling element bearing fault detection, ISA Trans., 50 (4) (2011) 599–608.
[66] A. S. Raj and N. Murali, Early classification of bearing faults using morphological operators and fuzzy inference, IEEE Trans. Ind. Electron., 60 (2) (2013) 567–574.
[67] M. E. H. Benbouzid, Bibliography on Induction Motors Faults Detection and Diagnosis, 14 (4) (1999) 454–459.
[68] W. Z. W. Zhou, T. G. Habetler, and R. G. Harley, Stator Current-Based Bearing Fault Detection Techniques: A General Review, IEEE Int. Symp. Diagnostics Electr. Mach. Power Electron. Drives, (2007) 7–10.
[69] W. Kruger, Tracking Rolling Element Bearing Failures Using Mechanical and Electrical Vkbration Testing Method, no. 860.
[70] C. Harlisca, L. Szabo, L. Frosini, and A. Albini, Diagnosis of rolling bearings faults in electric machines through stray magnetic flux monitoring, 8th Int. Symp. Adv. Top. Electr. Eng. ATEE 2013.
[71] M. S. Yilmaz and E. Ayaz, Adaptive neuro-fuzzy inference system for bearing fault detection in induction motors using temperature, current, vibration data, (2009) 1140–1145.
[72] J. Liu, W. Wang, and F. Golnaraghi, An enhanced diagnostic scheme for bearing condition monitoring, IEEE Trans. Instrum. Meas., 59 (2) (2010) 309–321.
[73] http://csegroups.case.edu/bearingdatacenter/pages/welcome-case-western-reserve-university-bearing-data-center-website.
[74] http://csegroups.case.edu/bearingdatacenter/pages/apparatus-procedures.