

ROTOR SPEED-BASED BEARING FAULT DIAGNOSIS (RSB-BFD) UNDER VARIABLE SPEED AND CONSTANT LOAD

*Pankaj Yadav, *Er. Gunjeetpal Singh
*M. Tech, Research Scholar, GZSCCET, Bathinda
**Assistant Professor, GZSCCET, Bathinda

Abstract

This paper addresses the application of rotor speed signal for the detection and diagnosis of ball bearing faults in rotating electrical machines. Many existing techniques for bearing fault diagnosis (BFD) rely on vibration signals or current signals. However, vibration- or current-based BFD techniques suffer from various challenges that must be addressed. As an alternative, this paper takes the initial step of investigating the efficiency of rotor speed monitoring for BFD. The bearing failure modes are reviewed and their effects on the rotor speed signal are described. Based on this analysis, a novel BFD technique, the rotor speed-based BFD (RSB-BFD) method under variable speed and constant load conditions, is proposed to provide a benefit in terms of cost and simplicity. The proposed to implement Hilbert transform and wavelet transform on Rotor Speed-Based Bearing Fault Diagnosis. To make the proposed algorithm more adequate in real environment, it is also necessary to improve the ability of distinguishing the fault from other sources of speed oscillation.

Index Terms: Bearing fault diagnosis (BFD BFF, ORF, IRF and BBF, rotor speed, sum square error, variable speed.

I. INTRODUCTION

Fault designation techniques have become additional necessary as additional engineering processes square measure automatic whereas the personnel required to control and supervise processes is reduced. as a result of rotating electrical machines (REMs) square measure at the center of most engineering processes and square measure designed for tighter margins, there's a growing want for fault designation for the sake of dependableness. Completely different faults could occur in a very REM, which may be classified as mechanical device faults, rotor faults, static and dynamic eccentricities, and bearing faults [1]. Supported Associate in Nursing IEEE motor dependableness study for giant motors higher than two hundred hp[2], bearing faults square measure the foremost important single explanation for motor failure (41%), followed by mechanical device faults (37%) and rotor faults(10%). In fact, rolling bearings square measure used not solely in motors however additionally in nearly each process that involves rotating and reciprocal machinery [3].

Existing techniques for bearing fault designation (BFD) need additional knowledge acquisition instrumentation and extra measurements, like vibrations, temperature, acoustic emissions, and mechanical device current watching [4]. Particularly, recent surveys [5]–[1] indicate a transparent tendency toward the vibration watching of REMs. However, despite the very fact that vibration-based BFD techniques are with success applied and

square measure more and more deployed in trade [1]–[4], challenges still exist that has to be addressed . Vibration sensors, like accelerometers, square measure mounted on the surface of system elements, that square measure put in deep within machinery and square measure tough to access throughout data processing. The sensors and instrumentation are inevitably subject to failure that might cause extra issues with system dependableness and lead to extra in operation and maintenance prices [15]. Moreover, within the case of variable speeds, the vibration signal from the bearings is littered with operation, that makes designation tough. These difficulties square measure attributable to the variation of diagnostic options caused primarily by speed variations, low energy of sought-after options, and high noise levels. As an alternate, many researchers [5]–[7] have projected mechanical device current-based techniques beneath the idea that the machine operates at a continuing provide frequency at steady state. sadly, this assumption is also impractical in Associate in Nursing actual system. mechanical device current-based approaches additionally suffer from the very fact that mechanical device current signals will be used providing there's an outsized failure. Note that the detection of a very early inchoate fault is important in BFD as a result of a minor bearing fault will speedily become a significant failure. To overcome the challenges with existing BFD techniques supported vibration or mechanical device current signals, this explores the appliance of a rotor speed signal to the detection and designation of roller bearing faults (BBFs) in REMs.

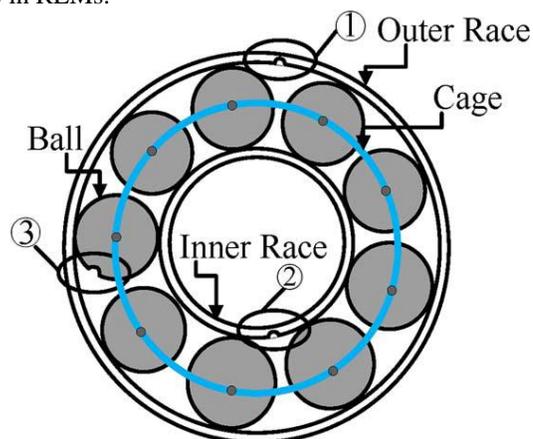


Fig. 1. Ball bearing geometry and the possible defects

The projected rotor speed-based BFD (RSB-BFD) methodology assumes variable rotor speed conditions and solely uses rotor speed measurements. Since speed signals square measure reliable and simply accessible as compared to vibration signals, this approach will be helpful inters of low value, simplicity, and

dependableness. However, it's necessary to notice that the frequency domain analysis of a speed signal shows no important distinction between completely different bearing faults, that is that the primary reason why rotor speed based mostly BFD has not been used. to resolve this drawback, we have a tendency to propose absolutely the value-based principal element analysis(PCA) (AVPCA), during which the classical PCA, a well known feature extraction methodology, is changed to calculate the PCA bases victimisation absolutely the price of weights and therefore the add sq. error distances.

Bearing Fault Types

Based on the fault classification in [7], bearing faults can be categorized into two types: 1) single-point faults, which are defined as a visible single fault; and 2) generalized roughness, which refers to a damaged bearing. A single-point fault produces a characteristic fault frequency that depends on the surface of the bearing that contains the fault. Because most rotating machines use rolling-element bearings that consist of an outer race and an inner race, single-point faults in a bearing considered in this study include the following: 1) outer-race fault (ORF); 2) inner-race fault (IRF); and 3) ball bearing fault (BBF), as shown in Fig. 1. The bearing fault-free case is denoted by BFF. A bearing fault introduces specific frequency components that depart from the normal distribution, which subsequently increases the kurtosis value. Fault-related torque oscillations at particular frequencies are often related to the shaft speed. The characteristic bearing fault frequency f_c in different bearing faults is given by the following relationships [1]:

$$f_c = \begin{cases} f_{out} = \frac{N_b}{2} f_r \left(1 - \frac{d_b \cos \beta}{d_p} \right) & \text{for ORF} \\ f_{in} = \frac{N_b}{2} f_r \left(1 + \frac{d_b \cos \beta}{d_p} \right) & \text{for IRF} \\ f_{ball} = \frac{d_p}{d_b} f_r \left(1 - \left(\frac{d_b \cos \beta}{d_p} \right)^2 \right) & \text{for BBF} \end{cases}$$

Where f_{out} is the ORF frequency, f_{in} is the IRF frequency, f_{ball} is the ball fault frequency, d_b is the ball diameter, d_p is the pitch ball diameter, N_b is the number of balls, β is the ball contact angle (with the races), and f_r is the mechanical rotor frequency.

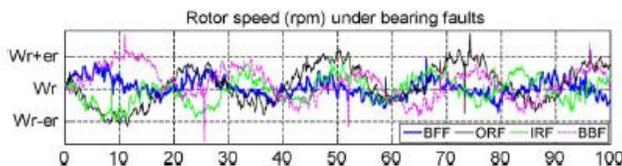


Fig. 2. Measurements of the rotor speed under constant load for different bearing faults with $T_s = 58.61 \mu s$, $w_r = 2500$ r/min, and $er = 10-4$.

II. BIORTHOGONAL POSTERIOR VIBRATION SIGNAL-DATA PROBABILISTIC MOVING RIDGE NEURAL NETWORK

Major industrial drive is fascinated by constructing the induction motor with none transient disturbance whereas dashing up the motor speed. the most goal during this work is to construct a Biorthogonal moving ridge rework mistreatment the vibration signal-data of the economic drive. The moving ridge rework

represent the vibration signal-data at the same time at time 't' with a frequency 'f'. Biorthogonal analysis of the wavelets decomposes the vibration signal-data into frequency and conjointly the time issue on that the frequency gets fluctuated. BPPVS-WNN system frequency vary is maintained with none transient disturbance and conjointly achieves higher fault detection on the induction motor with token execution time with elaborated constant obtained until fifth by-product type. The Biorthogonal moving ridge rework in BPPVS-WNN system is illustrated in Figure 1.

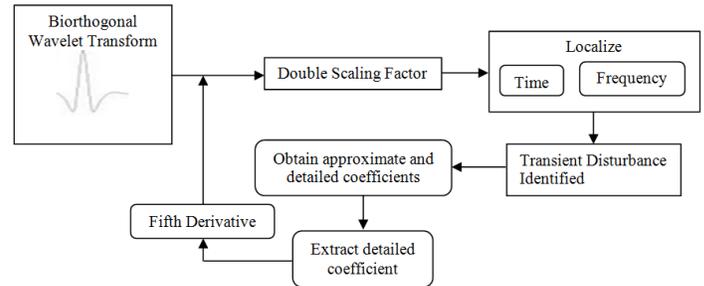
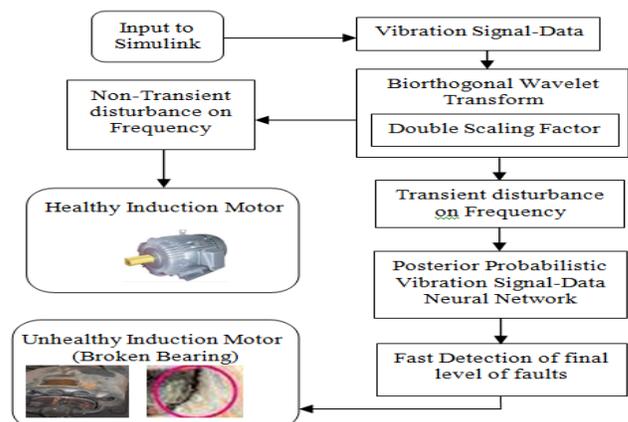


Figure 3. Procedural step of biorthogonal wavelet transform

The Biorthogonal wavelet transform with vibration signal-data is used to easily localize the time and frequency domain. The time and frequency domain variation point help to easily detect the broken bearing in the induction motor. The detection of broken bearing is based on the transient disturbance on the frequency value. The FD approximate and detailed coefficients are computed using Biorthogonal Wavelet Transform. The overall diagrammatic form of proposed BPPVS-WNN system is illustrated in Figure 2. The overall structure of the Biorthogonal Posterior Vibration Signal-Data probabilistic Wavelet Neural Network is presented. The vibration signal-data of induction motor is taken as the input parameter using the Simulink MATLAB code. The vibration data are analyzed rough the Biorthogonal Wavelet Transform.



The wavelet transform carries out the double scaling factor which localized the time and frequency domain. The nontransient disturbance on the frequency range (i.e., 50 Hz), then the healthy induction motor is used on the industrial drive with maximal speed rate. Biorthogonal Wavelet varies based on the frequency domain, and then the fault occurred on the induction motor is measured. The fault in the induction motor is

measured based on the broken bearing using the Posterior Probabilistic Vibration Signal-Data Neural Network. The broken bearing detection through neural network in BPPVS-WNN System results in two coefficient values called the approximate coefficient and detailed coefficient. The detailed coefficient value is applied until fifth derivative is obtained. Posterior Probabilistic Wavelet Neural network combine the theory of the fifth derivative wavelets and neural networks into one to feed-forward neural network to identify the faults in the induction motor at a faster rate.

III. LITERATURE SURVEY

Moussa Hamadache, et al (2015). during this study, addresses the applying of rotor speed signal for the detection and designation of bearing faults in rotating electrical machines. several existing techniques for bearing fault designation (BFD) accept vibration signals or current signals. However, vibration- or current-based BFD techniques suffer from varied challenges that has got to be addressed . As another, this paper takes the initial step of work the potency of rotor speed watching for BFD. The bearing failure modes ar reviewed and their effects on the rotor speed signal ar delineated . supported this analysis, a unique BFD technique, the rotor speed-based BFD (RSB-BFD) technique underneath variable speed and constant load conditions, is projected to supply a profit in terms of price and ease. The projected RSB-BFD technique exploits absolutely the value-based principal element analysis (PCA), that improves the performance of classical PCA by exploitation absolutely the worth of weights and therefore the total sq. error. The performance ANd effectiveness of the RSB-BFD technique is incontestable exploitation an experimental setup with a collection of realistic bearing faults within the outer race, inner race, and balls. [1].

K. Jayakumar, et al (2015). have projected work to sight broken bearing faults in induction machine. to get an efficient fault detection of commercial drives, Biorthogonal Posterior Vibration Signal-Data Probabilistic wave Neural Network (BPPVS-WNN) system was projected during this paper. this technique was centered to reducing this flow and to spot faults with lesser execution time with harmonic values obtained through fifth by-product. Initially, the development of Biorthogonal vibration signal-data based mostly wave remodel in BPPVS-WNN system localizes the time and frequency domain. The Biorthogonal wave approximates the broken bearing exploitation double scaling and issue, identifies the transient disturbance thanks to fault on induction motor through approximate constants and elaborated coefficient. Posterior Probabilistic Neural Network detects the ultimate level of faults exploitation the elaborated constant until fifth by-product and therefore the results obtained through it at a quicker rate at constant frequency signal on the commercial drive. Experiment through the Simulink tool detects the healthy and unhealthy motor on measurement constant quantity factors like fault detection rate supported time, current rate of flow and execution time.[2]

Ming Zhao, et al (2015). once in operation underneath harsh condition (e.g., time-varying speed and cargo, giant shocks), the vibration signals of rolling part bearings ar continuously manifested as low signal noise quantitative relation, non-stationary applied math parameters, that cause difficulties for current diagnostic strategies. As such, AN IMF-based adaptative envelope order analysis (IMF-AEOA) is projected for bearing fault detection underneath such conditions. This approach is established through combining the ensemble empirical mode decomposition (EEMD), envelope order pursuit and fault sensitive analysis. during this theme, EEMD provides an efficient thanks to adaptively decompose the raw vibration signal into IMFs with completely different frequency bands. The envelope order pursuit is additional utilized to remodel the envelope of every International Monetary Fund to angular domain to eliminate the spectral smearing elicited by speed variation, that makes the bearing characteristic frequencies a lot of clear and discernible within the envelope order spectrum. Finally, a fault sensitive matrix is established to pick out the optimum International Monetary Fund containing the richest diagnostic data for final decision-making. The effectiveness of IMF-AEOA is valid by simulated signal and experimental information from locomotive bearings. The result shows that IMF-AEOA may accurately establish each single and multiple faults of bearing even underneath time-varying rotating speed and huge extraneous shocks. [3]

Hongmei Liu1, et al (2013). The fault designation exactitude for rolling bearings underneath variable conditions has continuously been disappointing. For determination this downside, a feature extraction technique hairdressing the Hilbert-Huang remodel with singular worth decomposition was projected during this paper. the tactic includes 3 steps. Firstly, instant amplitude matrices were obtained by Hilbert-Huang remodel from rolling bearing signals. Secondly, because the fault feature vector, the singular worth vector was noninheritable by applying singular worth decomposition to the instant amplitude matrices. Thirdly, the identification and classification of rolling bearing were achieved by Elman neural network classifier. The experiment shows that this technique will effectively classify the rolling bearing fault modes with high exactitude underneath completely different in operation conditions.[4]

IV. PROBLEM FORMULATION

In the rotor motor fault identification of rotating machinery is that the major downside in today's world. The first EMD algorithmic program is that's applied in previous work isn't good. one in every of the main drawbacks of EMD is that the mode admixture downside, that not solely results in serious aliasing in time-frequency distributions, however additionally makes the physical meanings of individual IMFs unclear the rotation speed of wheel (as well because the outer-race) cannot keep constant within the take a look at, the smearing downside happens within the envelope spectrum. Basic Vibration Signal process (BVSP) self-addressed the issues associated with detection of faults within the bearing at associate degree early stage applying AM and mathematician remodel. the advance of dependability issue

of mechanism system by diagnosis the faults of rolling part is very vital as breakdowns on bearing square measure the foremost frequent issues associated with rotating machinery. The sensors and instrumentality are inevitably subject to failure, that may cause further issues with system dependability and end in further operational and maintenance prices. The frequency domain analysis of a speed signal shows no vital distinction between completely different bearing faults, that is that the primary reason why rotor speed based mostly BFD has not been used.

V. RESEARCH METHODOLOGY OVERVIEW

The work is for rotor motor fault diagnosis. It is based upon GUI (graphical user interface) in MATLAB. It is an effort to further grasp the fundamentals of MATLAB and validate it as a powerful application tool. There are basically different files. Each of them consists of m-file. These are the programmable files containing the information about the motor related data. The Biorthogonal Wavelet Transform 'BWT' initially obtains the approximated and detailed coefficient values. To obtain the fifth derivative (FD) form, our work proposed system uses the detailed coefficient value 'D'. This 'D' value is iterated five times. The fifth derivative form is the final output obtained through BWT. In a similar manner, BPPVS-WNN system takes the approximated coefficient value once and detailed coefficient value with the fifth derivative form of 'N' induction motors of the industrial drive. Biorthogonal Transform using time and frequency wavelets and identify the faults.

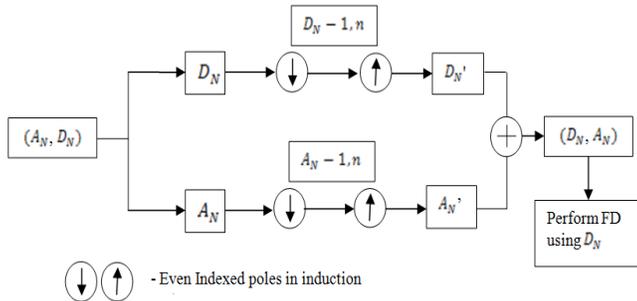


Figure 4. Biorthogonal wavelets with coefficient and approximated values

VI. CONCLUSION & FUTURE SCOPE

In this paper I have studied different authors work. Each author have some problems these are given above. In this paper the first EMD algorithmic program is that's applied in previous work isn't good. one in every of the main drawbacks of EMD is that the mode admixture downside, that not solely results in serious aliasing in time-frequency distributions, however additionally makes the physical meanings of individual IMFs unclear the rotation speed of wheel (as well because the outer-race) cannot keep constant within the take a look at, the smearing downside happens within the envelope spectrum. In the I will propose algorithm more adequate in real environment, it is also necessary to improve the ability of distinguishing the fault from other sources of speed oscillation. To improve the fault detection and fault diagnosis performance & calculate the parameters like BFF,ORF, IRF and BBF etc..

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