Review On Condition Monitoring Of Rotating Machines

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Abstract: Identifying the defects in the bearings is very much essential for condition monitoring. In this paper, various bearing condition monitoring Techniques were reviewed briefly. Specifically, the reviewed bearing condition monitoring methods include acoustic emission, surface roughness, and vibration monitoring

Key words: Acoustic Emission, Bearings, Condition monitoring, Surface roughness, Signal parameter, Vibration.

1. INTRODUCTION

Acoustic Emission (AE) technique show increasing attention as a complementary method for condition monitoring of bearings due to very sensitive in identifying the basic defects compared to vibration based measurement techniques. The present work investigates the AE characteristics of bearing defects and validates the relationship between various AE parameters. Various study utilized several techniques to monitor the performance of ball bearing, still exact prediction was highly impossible[1]. Analyzed vibration signals of the single and multiple point defects of the bearings using discrete wavelet transform (DWT) technique. Also they introduced a new approach to achieve 99% bearing defect monitoring using Hidden Markov Models (HMMs)[2]. analyzed the 6220 deep grove ball bearing having different sizes of defects with different speed and load conditions includes 0kN, 3kN, & 7kN and found that an increase in defect size, amplitude, energy level but kurtosis value was increased initially and then it decreased[3]. compared AE signals and vibration signals over a range of speed and load conditions with good bearing and defected bearing with outer race of the bearing and concluded that the vibration spectrums doesn't have the clarity in its peak raising at defect frequency whereas AE spectrums provide a clear peak at defect frequency[4]. experimentally identified the defects in the outer race of the bearing using vibration signals and stator current signals for the bearing of an induction motor with constant speed and varying load conditions[5]. Concluded that the acoustic emission was the best technique to identify the defects[6]. Investigated the effect of the bearing defect size and its location by analytical model. Numerical results for 6305 deep groove ball bearing had been obtained and discussed. The percentage variation between the theoretical and experimental defect frequency was 4.5%–5.6%[7]. Investigated the fault diagnosis of ball bearings with combination of defects using artificial neural network (ANN) and support vector machine (SVM) for deep grove ball bearing with different speed and loading conditions. Analytical Wavelet Transform (AWT) was utilized to identify the presence and severity of defects in the inner race of bearing[8].

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Analyzed the acoustic and vibration signals of the radial bearing having inner race defect and it had been processed with a signal processing technique to measure the defect width with time duration of 0.5 sec for the healthy and defective bearing. The acoustic and vibration signal of defective bearing had higher RMS, SD, kurtosis, and crest factor but has lower skew-ness and SNR than the healthy bearing which indicated the presence and severity of defects[9]. Simulated the defects in the roller and inner race of the bearings with the help of spark erosion method. The small size defects in the inner race and roller of the bearings were identified using ring down counts of acoustic emission signal. It was concluded that as the defect size increases, more events were emitted with higher values of peak amplitudes and ring down counts[10]. Experimentally investigated the bearings using three loads i.e. for 0.1kN, 4.43kN and 8.86kN with four different speeds like 600, 1000, 2000 and 3000 rpm using AE signals for identifying the presence and size of a defect[11]. Reviewed the acoustic measurement techniques like sound pressure, sound intensity and acoustic emission. Wavelet transform method and automated data processing technique were also reported to identify the defects in bearing. The frequency domain signals were used to detect the location of the defect. Wavelet transform method had used to extract very weak signals and concluded that acoustic emission measurements can detect a defect even before it appears on the surface[12]. Analyzed the single and multiple point defects on outer race, inner race of the bearing using discrete wavelet transform (DWT). They concluded that DWT can be used as an effective tool for detecting the single and multiple faults in the ball bearings[13]. Investigated the vibration parameters like RMS, peak, crest factor, power and cep-strum of the vibration signal of the bearings with defects of different sizes and compared with good bearings[14]. Investigated the effectiveness of two ultrasonic sensors, which were air-coupled and piezoelectric ultrasound transducers for rolling element bearings damage diagnostics. The former was a noncontact sensor and the latter was a contact sensor[15]. Investigated the effects of the size of the ball bearing and cylindrical roller bearing on the maximum eccentricity ratio. The result shows that the maximum eccentricity ratio was affected by the clearance constraint and contact deformation of the rolling bearing[16]. Performed experimental analysis on cylindrical roller bearing with smearing damage. The experimental goal was to compare the wear protection afforded by various surface treatments, including vibratory super finishing, black oxide treatment, and special tungsten carbide–reinforced amorphous hydrocarbon roller body coatings[17]. Carried out the experimental investigation to study the changes in the

signal parameters for bearings in good condition and with simulated defects in the outer race of the bearings of an induction motor. The experimental analysis was done using stator current harmonics measurement in combination with vibration, AE and SPM condition monitoring techniques. The measurements were carried out from no load to full load (27 kg) for the induction motor bearing with an increment of 5 kg[18]. The Multi-features entropy distance (MFED) is roller bearing diagnosis method in this diagnosis process with the single and double faults by entropy integration such as SSE - time domain, PSE – frequent domain, WSSE and WESE in time and frequent domain with vibration and AE signals[19]. Acoustic spectral imaging is bearing diagnosis method, when the bearing diagnosis is depend on detecting the frequency defect. In this method have certain risk, for example, the speed of non-stationary shaft creates a frequency defect by impact and also variations of shaft speed that results to tiny variations on frequency defects[20]. cestrum pre-whitening (CPW) is bearing condition detecting method by using two different instruments: vibration and acoustics emission (AE). These methods detect the fault at middle and last stages. This signal analysis in between vibration and AE. Initially peaks erase by the RMS filter over a multiple of RMS value to the actual signals and seconds. Logarithmically expands the compression filter the low magnitude waveforms[21]. The contamination paticles are in rolling bearing are detect by using acoustic emission (AE) method. The detection of contamination particles in these bearing was only applicable for high speed rotational at above 300 rpm[22]. the different bearing faults patterns is classifies effectively at low speed and at different load conditions by support vector machines (SVM) for genetic algorithms (GA) and regression[23]. The different bearing faults patterns is classifies effectively at low speed and at different load conditions by support vector machines (SVM) for genetic algorithms (GA) and regression[24]. The dynamic and rolling element finite values are identify by visual basic programming. It is help to reduce the time. The defective structure in analysis by the frequency and structure monitor is find the non-defective and defective bearing identity by the frequency test. In this vibration signal are tested to find defective bearing .The software test is used in rolling element bearing[25]. Identify defect by wave form and noisy signal to detecting key problem of the bearing also the mixture de-noisy techniques is used to improve the signal and condition of the wave form. The different noise wave is used to identity different size of bearing and noise ratio[26]. The acoustic emission wave form is used to check bearing characterizing the defect size of loading area of bearing. It is identify by varies defect size of the inner and outer races of test bearing. It check actual tested sizes of the bearing and totally used to identify outer races of bearing[27]. In the correlation integral is developed for machine vibration and life test of rolling element bearing. The test is taken by computer output and the algorithm is increase the time and reduce defective bearing identify by using computer analysis[28]. The low speed bearing which developed to the identify various defects of the bearing and low speed of 10 rpm is used for this operation .It can help to identify bearing problem with the low speed testing for the machine[29]. The acoustic emission technology is used for identify and detecting the location of natural defects occurs in ball bearing elements .the crack initiation in sub surface and crack propagation in subsequent can be identified using range data provide from acoustics emission from the defective bearing [30]. In this method bearing is monitor by the continuous wavelet techniques. It is used for identification of bearing defects. The bearing failure may be occurs at four part such as inner race fault outer race fault cage fault and ball fault. Analysis the fault of inner races and outer race fault of ball bearing by continuous wavelet techniques[31]. Monitoring bearing by the vibration indicator. In this method divide into three stages. The first stage is analysis different vibration signal at simulated defect occur. The second stage is test and analysis the perception of noise elated by the defect it result to calculate value of sound perception .The final stage is study the dimension representation of deterioration of simulated defects. It is more efficient than the isolated classical indicator[32]. Chatter is a fast-converting machining error that needs to be timely analyzed to avoid the weakening. However, it is a big experiment to identify the weak chatter part out of the machining process signal that comprises strong troubles caused by the measurement noise, the machining hesitate in the later stage [33]. The precision of the vibration reaction recreated by the dynamic model of the inadequate bearing relies upon the exact articulation of the connection between the moving components furthermore, imperfection zone in the model. An improved unique model considering the three dimensional geometric connection between the moving component and the imperfection zone is created to research the unexpected difference in contact power and the comparing vibration signal of the bearing system[34]. Dynamical demonstrating of a rigging framework with deficiencies has been a significant research theme for understanding issue highlights and their related deficiency vibration components. Due to the confused structures and many-sided cooperation between the parts of the rigging framework, the flaw vibration includes and comparing vibration systems because of tooth setting furthermore, spilling remain for the most part obscure [35]. The contact coefficient is decreased as the speed of the pole unrest increments inside the system in which static grinding is prevailing. For this situation, the pole bearing framework can wind up precarious because of the stick-slip movement of the shaft bearing framework, and self-energized vibration can happen. In this examination, the pole bearing framework is portrayed utilizing a two degrees of opportunity model, and a security investigation is performed as system parameters such as ordinary burden, damping on the bearing, and the regular recurrence of the pole framework identified with the stick-slip movement at the pole bearing interface [36]. Defects on gear, shafts for transmission and drivetrains are basic in hardware, for example, airplanes and helicopters. On-going condition observing of these segments, utilizing prescient upkeep procedures is henceforth a proactive errand. For compelling force transmission and most extreme administration life, gears are required to stay in perfect arrangement however this errand is simply past the limits of probability. These segments are adaptable, in this manner regardless of whether impeccable arrangement is accomplished; irregular unique powers can cause shafts to twist causing gear misalignments [37]. The angular position of the external ring shortcoming affects the remaining life and the activity execution of metal ball. Along these lines, the acknowledgment of the restriction analysis of the external ring flaw is vital to the bearing execution debasement evaluation and the existence expectation [38]. Acoustic emanation (AE) is utilized for the condition observing and shortcoming finding of different parts like apparatus, bearing, machine device and so

forth. The exploratory investigations have been introduced which demonstrates the capacity of AE to blame/imperfection location on course. The nearness of deformity impacts the AE esteem [39]. A relationship between rigging wear in spike gears and the factual properties of AE signals. A summed up Gaussian cyclo-stationary model is proposed for AE sign estimated on riggings. This decision is spurred by the attributes of greased up contact in spike gears, joining non-stationary (for example cyclo-stationarity) and non-Gaussianity [40]. The previous is because of the cyclic kinematics of rigging tooth coinciding, which prompts a periodicity in the insights of the AE signal, while the last is brought about by fast vitality discharge from acrimony twisting during rigging tooth contact. Moving component course are normally utilized in rotatory machines and their activity conditions should be observed to counteract calamitous disappointments. A successful internet observing technique to examine wear seriousness and wear instruments of direction. For this reason, morphological highlights of wear trash from heading, including amount, shading, size and shape, are separated from recordings of moving particles conveyed in grease oil [41]. The ability of machine learning model was calculated by three factors: Correlation coefficient, Spearman Rho's, and Mean absolute error for fillers as Copper Slag, Fly Ash, and High Calcium Fly-Ash. Support vector machine with PUK kernel emerges as the best analyst both for training and testing, since it is providing a high reading of Correlation coefficient and Spearman Rho's and least Value of Mean absolute error for all the investigational cases considered. After SVM-PUK, SVM-RBF gives better result followed by SVM-P, ANN-RBF, and Isotonic Regression respectively [42]. Pseudo-defective signals, two signals are coupled with of both defective parts and healthy parts, may lead to non-diagnosis for good component. It is a challenging mission to decouple pseudo-defects parameters based on the single-channel pseudo-defective signal of spinning machinery. An issue is presented for feature filtration of the pseudo-defective signal of a rolling parts bearing (REB) in a spinning-bearing system. To address the matter, a method is concluded for feature of a REB pseudo-defect in a rotor-bearing system established on spectral degree of cyclo-stationarity (DCS) [43].

2 SUMMARY OF LITERATURE SURVEY

From the literature collection it is clear that the acoustic emission technique (AET) is more sensitive than the vibration analysis. Also the Acoustic emission and vibration parameters like Amplitude, RMS, count, event, kurtosis are dependent on the operational conditions like defect size, load, speed, number of balls, viscosity and radial clearance.

3 CONCLUSION

By monitoring the bearing which identify the defects like inner race, outer race and cage. Hence the defects of the bearings are identified with the help of signal parameters for the sound and vibration signals.

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