Fault Detection Using Vibration Analysis and Particle Swarm Optimization of Rolling Element Bearing

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Abstract. The bearing's relevance, technical uses are clear in many applications. It is subjected to various types of loading. The rolling bearing may be cracked because of fatigue loading. The presence of a crack causes a change in the physical properties of a bearing and thus reducing the stiffness of the rolling bearing, where the invisible natural frequencies are being reduced. The essential signatures of vibration of bearing analysis are crack depth and location. The current study used Finite Element Analysis (FEA), experiments data and Particle Swarm Optimization (PSO) technology to create methodologies for fracture detection of a solitary crack in a rolling bearing. Different crack location effects are taken into account, and the results are compared to different rolling bearing crack depths. Then PSO algorithm has been developed using the first three relative natural frequencies taken from FE analysis and experiments data. For comparative study, both Standard PSO and APSO are used for crack diagnosis of the bearing. The feasibility of proposed PSO techniques is compared through error analysis. The research paper, the objective has been related to the design of a Particle swarm optimization technique for more accuracy and less time consumption to the prediction of crack location and crack depth in cracked bearing.

Keywords: Vibration, bearing, Crack, natural frequency, PSO

1 Introduction

The bearing components of any rotating machine is one of the major components of all type of technology mechanical power transmission systems. The failure of the bearing due to fatigue caused the breakdown of the whole production line. Condition monitoring and the diagnosis of bearing fault are used to extract information from signals which are characteristics of the certain fault mechanism. The advanced artificial intelligence techniques for diagnosis the accurate fault locations. The primary objective is to develop the bearing's fault at an incipient stage. The diagnosis process should be robust and able to operate effectively under system noise.

Damage occurs in the bearing then there is a change in its dynamic properties and natural frequency, and also there is an increase in modal damping and variation of the modal shapes. Here, PSO is a bio-inspired population-based evolutionary optimisation method that uses swarm intelligence to attain its objective of the optimization. Kennedy and Eberhart [1] presented a technique that can optimize non-linear functions by the use of a particle swarm and defined a relationship among both artificial and genetic algorithms and particle swarm by executing on a model. Li et al. [2] presented a method that can identify any fault in the roller bearing of a motor with the help of neural networks & vibration assessment on the time-frequency domain. In the paper concluded that neural networks along with real-time experimental results can be very effective in bearing fault identification. Qiu et al. [3] have focused on signal denoising approaches and compared the performance of the two most used techniques, which are created on wavelet decomposition and wavelet filter on defect signals, and concluded that wavelet filter is more consistent by executing these methods on both simulation & trial information.

De-noising and extraction of the weak signature are crucial to fault prognostics in which case features are often very weak and masked by noise. The wavelet transform has been widely used in signal de-noising due to its extraordinary time-frequency representation capability. Here, the performance of wavelet de-composition-based de-noising and wavelet filter-based de-noising methods are compared based on signals from mechanical defects. The comparison result reveals that wavelet filter is more suitable and reliable to detect a weak signature of mechanical impulse-like defect signals, whereas the wavelet decomposition de-noising method can achieve satisfactory results on smooth signal detection. To select optimal parameters for the wavelet filter, a two-step optimization process is proposed. Minimal Shannon entropy is used to optimize the Morlet wavelet shape factor. A periodicity detection method based on singular value decomposition (SVD) is used to choose the appropriate scale for the wavelet transform. The signal de-noising results from both simulated signals and experimental data are presented and both support the proposed method. De-noising and extraction of the weak signature are crucial to fault prognostics in which case features are often very weak and masked by noise. The wavelet transform has been widely used in signal de-noising due to its extraordinary time-frequency representation capability. Here the performance of wavelet decomposition-based de-noising and wavelet filter-based de-noising methods are compared based on signals from mechanical defects. The comparison result reveals that the wavelet filter is more suitable and reliable to detect a weak signature of mechanical impulse-like defect signals, whereas the wavelet decomposition de-noising method can achieve satisfactory results on smooth signal detection. In order to select optimal parameters for the wavelet filter, a two-step optimization process is proposed. Minimal Shannon entropy is used to optimize the Morlet wavelet shape factor. A periodicity detection method based on singular value decomposition (SVD) is used to choose the appropriate scale for the wavelet transform. The signal de-noising results from both simulated signals and experimental data are presented and both support the proposed method. Antoni and Randall [4] have used spectral Kurtosis (SK) for the health monitoring of rotary components by sensing unstable vibration signals and proposed a kurtogram in which the optimal band pass filter could be determined. They have explained these methods using real-life situations. Antoni [5] has tried to formalize the Spectral Kurtosis (SK) with the help of short time Fourier transform-based method to relate theoretic concepts with hands-on applications. Zarei and Poshtan [6] have used stator current as the parameter for the health monitoring of bearing in Induction Motors by comparing energy differences as a fault indicator. It is shown the dominance of this method by effectively executing experimental signals. Sawalhi et. al [7] have presented an algorithm to enrich the Spectral Kurtosis (SK) by combining the Minimum entropy deconvolution (MED) system and show the dominance of this method by executing on a test rig and gearbox bearings successfully. Nanda et al. [8] have presented a method to locate the crack, centred on incremental Particle Swarm Optimization (PSO) and compared with standard PSO. They concluded that the method can detect and estimate the extent of the damage by formulating objective functions from finite element simulation. Qian et al. [9] have presented HOA which stands for hybrid optimization algorithm with the combination of particle swarm optimization (PSO) and the simplex method (SM) to resolve the nonlinear optimization problem and executed this on different examples of separation along a plane. Kishore et al. [10] have used distribution information of the population to estimate evolutionary states and developed Adaptive PSO (APSO) so that optimization problems can be solved and developed adaptive control strategies. Rane et al. [11] have presented a method based on the measurement of natural frequencies to locate and estimate the size of the crack in the cantilever beam. In this paper concluded the result based on finite element analysis of the beam having a crack and the beam having no crack.

2 Development of a Condition Monitoring System for signal processing

The following flow chart of the most commonly employed techniques in condition-monitoring applications of all types of bearings are as shown in Figure: 1

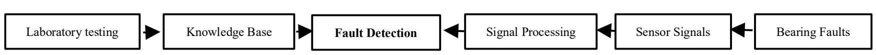

Fig. 1. Commonly employed techniques in condition monitoring

3 Vibration Model of Bearing

Any components without any defects in a machine usually generate light or no vibration during service. But when a small component of the machine fails, the vibration level and shape change at the whole system level. For these reasons, vibration signatures are the best signal of the overall machine condition. It is also the best diagnostic apparatus to detect the development of internal defects.

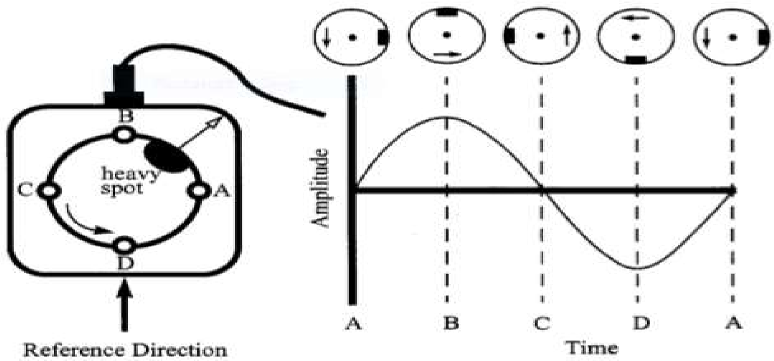

Fig. 2. An unbalanced bearing generates a sinusoidal Force and response waveform**.**

Fig. 3. Ball bearing with localized ball defect.

Figure 2 shows the behaviors of defective rolling elements in the cages of a bearing. This is the most common method for illustrating and representing vibration is the frequency spectrum. It is generally used to identify the source of vibration. Rolling element bearings consist of an inner race, outer race, ball, and cage which hold balls. Bearing failure often starts with a local defect on any of these elements. Figure 3 is an example of a ball bearing with a localized defect on the ball. When the defective ball rolls, it will generate repetitive impacts. The response can be measured by mounting an accelerometer on a supporting structure near the bearing.

The repetition frequency of the impulse train is determined by the location of the fault. These bearing-related frequencies are known as fundamental defect frequencies. The calculation of the fundamental frequencies of rolling element bearings is useful in machinery condition monitoring to detect the fault on the bearing. All rolling element bearings have four defect frequencies such as Ball pass frequency outer race (BPFO), Ball pass frequency inner race (BPFI), Ball spin frequency (BSF), and Fundamental train frequency (FTF). The relative Natural frequency (RNF) of all types of above frequency is calculated by the following equation.

$$\text{RNF}=\frac{Frequency\ of\ Healthy\ Bearing-Frequency\ of\ Defective\ Beaing}{Frequency\ of\ Hea\quad Bearing} \tag{1}$$

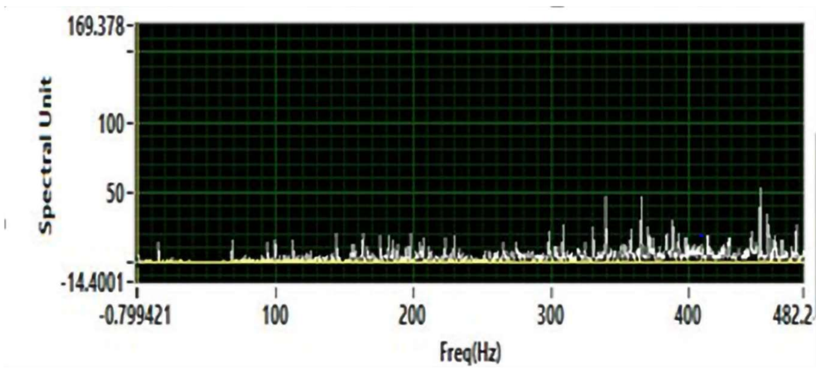

Fig. 4. Healthy bearing condition

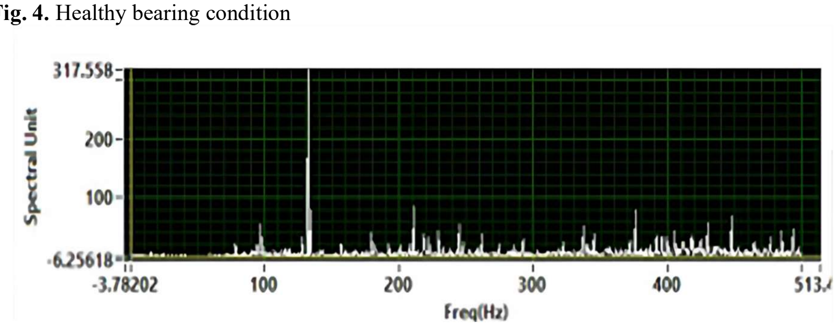

Fig. 5. Defective bearing condition

From the Figures 4 and 5. shows the healthy and defective frequency spectrum bearings. The rolling element bearing failure progress through the stages such as pre-failure, failure and near catastrophic failure stages. The bearing vibration characteristics of each stage are relatively different and complicated.

The objective of this study is to detect incipient bearing faults. Therefore, this technique is used to extract the small impulsive elements in the presence of vibration. After studying the failure stages and techniques to detect bearing faults, here focus on the high-frequency resonance technique. Figure 6 shows the variation of relative natural frequency in 1st mode with the relative depth of crack from the bearing surfaces. It shows that, the relative natural frequency increase with the relative depth of the crack. This show that if there is any defect present on any surface of the bearing, there will be a significate change in natural frequencies.

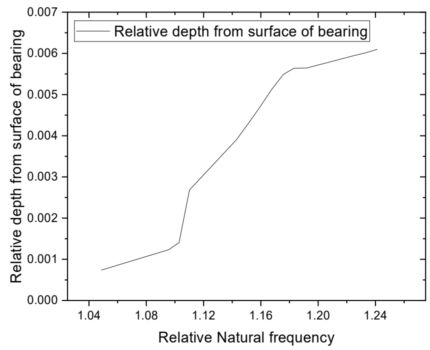

Fig. 6. Graph of Relative depth from the surface of bearing Vs Relative Natural frequency.

4 Methodology

Artificial intelligent approaches were created to estimate faults in structures faster and more accurately. Here they investigate the usage of optimization strategies such as Particle Swarm Optimization (PSO) for using vibration characteristics to diagnose single cracks in engineering constructions at an early stage. The vibration data, such as natural frequencies derived from finite element analysis, is used to determine the objective function for crack diagnostics. The PSO and APSO were employed to forecast relative crack depth and location. The PSO and a fuzzy adaptive PSO (APSO) were utilized, with the inertia weight dynamically altering based on the variation of population fitness. The feasibility of proposed PSO techniques is compared through error analysis.

4.1 Standard PSO

A swarm of M particles moves in a problem search area in the classic PSO paradigm. Each particle is a possible global optimum solution for a specific domain D.
The position of the i^{th} particle in N-dimensional search space is represented as

$X_i = (x_{i1}, x_{i2}, x_{i3}. \ . .x_{iD})$ which represents the particle's present location i $(1 \leq i \leq N)$ in a D – dimensional search space.

The new particle position is found at each generation k by modifying the existing position with a displacement, where the displacement is equal to a one-time step multiplied by the particle velocity, as indicated in Equation (2),

$$X_i^{k+1} = X_i^{k} + V_i^{k+1} \tag{2}$$

Where, X_i^{k+1} and X_i^{k} represent the present and the past position of the i^{th} particle respectively.
V_i^{k+1} is the current velocity of particle I denoted by

$$V_i = V_{i1}, V_{i2}, V_{i3} \dots\dots V_{iD} \quad (3)$$

At each generation, the velocity of each particle is also modified, and it can be written as,

$$V_i^{k+1} = V_i^k + C_1 \times r_1 \times (x_{pb}^k - x_i^k) + C_2 \times r_2 \times (x_{gb}^k - x_i^k) \quad (4)$$

Where, V_i^{k+1} and V_i^k represent the present and the past position of the ith particle respectively.

4.2 Fuzzy Adaptive PSO (APSO)

A dynamically modified fuzzy system can be used to change the inertia weight. Three rules made up the fuzzy system, which had one input and one output. The change in global best fitness standard deviation is used as an input, and the change in inertia weight is the output.

Equation (5) is used to represent the fitness function here.

$$F_i = \frac{1}{O_{th} + O_{bji}} \quad (5)$$

Where O_{th} is the threshold value, which can be anything between 0 and 1.0. In the current work threshold value has been perceived as 1 to eliminate singularity in the domain of solutions O_{bji} is the objective function taken from the selected data.

The inertia weight is revised by using Equation (6) to estimate the variance "σ^2" of the population fitness.

$$\sigma^2 = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{F_i - F_{avg}}{F_n}\right)^2 \quad (6)$$

Where F_i is the population's ith particle's fitness value.,

The median fitness value of a generation's population of particles is called F_{avg} and F_n is the normalizing factor taken as shown in equation 7,

$$F_n = \{\max|F_i - F_{avg}|\}, \ i = 1, 2, 3.......N. \quad (7)$$

The influence of a particle's past velocity on its current velocity is chosen at random using the above formulation, and the inertia weight is adjusted at random based on the variance of a population's fitness value. As a result, the particles' local and global searching capacities can be optionally coordinated.

4.3 Objective Function

The crack in a rolling element bearing causes a change in natural frequencies of vibration. The objective function as per relative natural frequency can be stated in Equation (8).

Minimize

$$\text{Obj} = K_0 + (K_1 \times RFNF) + (K_2 \times \text{RSNF}) + (K_3 \times \text{RTNF}) \quad (8)$$

Where, K_0, K_1, K_2, K_3 are the constants, RFNF, RSNF and RTNF are the Relative First, Second Third natural frequencies respectively.

Error Calculation

The performance study of standard PSO and APSO is presented in terms of % error and performance plot for cracked rolling element bearing. The error for different PSO techniques used for bearing has been calculated between the predicted and actual value as shown in Equation (8),

$$\% \text{ Error } = \left|\frac{\text{Predicated value} - \text{Actual value}}{\text{Actual value}}\right| \times 100 \tag{8}$$

5 Result and Discussion

In this research, the swarm optimization technique was used to diagnose the location and severities of cracks in rolling element bearing. The suggested modified PSO efficiently uses modifications in natural frequencies due to the existence of cracks to foresee structural damage detection. The result has been drawn from both standard PSO and APSO and analyses with the help of error analysis. A graphical representation has been shown in figure 7 for RCL and RCD respectively through error analysis.

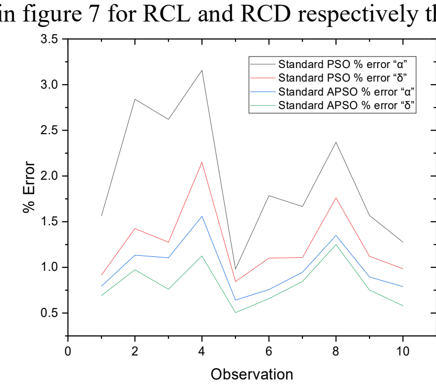

Fig. 7. Error analysis of PSO and APSO

Based on results obtained from finite element analysis, the APSO is shown to be linked to the least amount of error for prediction of the site of the crack and crack depth (0.642%, 0.505%) compared to standard PSO (0.981%, 0.845%) in a rolling bearing.

6 Conclusion

To compare the efficiency of regular PSO and APSO in identifying cracks, comparison is done. The result reveals that the APSO technique is more appropriate than standard PSO with minimum percentage error. It shows that this AI technique is a simple but robust methodology presented to determine the location and amount of crack in the rolling element bearing on the PSO technique.

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