Journal of Vibration Engineering & Technologies (2024) 12:6963–6977
https://doi.org/10.1007/s42417-024-01293-4

REVIEW

Recent Advancements in Fault Diagnosis of Spherical Roller Bearing: A Short Review

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Received: 8 June 2022 / Revised: 11 August 2023 / Accepted: 30 January 2024 / Published online: 21 March 2024
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Abstract

Purpose Early detection of bearing faults is an essential task of machine health monitoring. The bearings are one of the vital components of rotary machines. Various methods and techniques were used over the time to diagnose and improve the bearing fault analysis. This review paper includes a fourfold study on the fault analysis. First, the decomposition methods used for signal processing and extracting the required features are discussed under vibrational analysis for health monitoring. Second, the analysis on oil–air lubrication and thermal models used to study the temperature variations are studied. Third, analysis on sensor placement to select an optimal position in collecting the original signals with least possible disturbances was discussed in detail. Finally, in the fourth section, neural networks used for the fault diagnosis is reviewed and analysed.

Methods The convolutional neural network (CNN), Bayesian neural network (BNN), and probabilistic neural network (PNN) are the techniques most commonly used by researchers recently. Among the networks, CNN with modifications is found to provide high accuracy and robustness in identifying and classifying bearing faults even in noisy environments.

Results Discrete wavelet transform (DWT) method for the feature extraction. Daubechies four (db4) with five-layer decomposition method was used to identify the severity of bearing defects. Also, Orthogonal Fuzzy Neighbourhood Discriminant (OFND) features were extracted. This survey analysed existing works on fault diagnosis on spherical roller bearing in different perspectives.

Conclusion Among all the decomposition methods, variational mode decomposition was the most commonly used method and also found to be very effective compared to other methods. The intrinsic time scale method also finds a reasonable part in many research works. Also, various types of neural networks were used in which CNN and modifications to CNN were mostly used to automatically acquire the sensitive fault information from the decomposed signal data. The time-domain waveforms are used widely for feature extraction.

Keywords Fault diagnosis · Spherical roller bearing · Vibrational analysis · Sensor mounting · Neural networks · Thermal analysis

Introduction

The rolling contact bearings form an important component of rotary machines. The health condition of these bearings has a substantial effect on the performance of machines. A study on the fault diagnosis of rolling element bearing by Hoang and Kang exposed the importance of observing the health condition of the bearings to avoid failure of machines. The bearing faults are the major reason for 45–55% of broken machines [1]. The various kind of faults get exposed during the tireless operation of the machine. Once the fault appears, it will cause unscheduled downtime, economic loss and sometimes may lead to catastrophic accidents and

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casualties [2]. There are various types of faults that might occur in a bearing and some of them are due to the wear of the inner surface. This is frequently caused due to excessive load. The second flaw is the degradation of the circumference of the inner race. The other faults are caused by looseness in the self-aligning rolling element of the bearing [3].

With major developments in the extraction of relevant information from vibration signals, maintenance engineers could gradually be replaced by an autonomous detection procedure for diagnosing motor faults [3]. Deep Neural Networks (DNN) are widely utilised in image classification and, therefore, this method can scrutinise even minor changes that occur in feature extraction and still produce near accurate results. So, in an industry where the number of bearing faults under consideration is huge, it is preferable to use a deep network which can accurately predict the bearing fault. Deep neural networks were frequently used in picture classification, and as a result, the method could inspect even modest modifications in feature extraction, while still producing near-perfect results. However, big data generated from modern industry also offer an unprecedented opportunity to obtain an in-depth understanding of the machine condition. Therefore, it is vital to seize this opportunity and use advance diagnosis methods for accurate judgment [4].

Vibrational Analysis for Health Monitoring of Roller Bearing

Fault diagnosis techniques are very crucial for monitoring bearing conditions. A variety of methods and techniques used by various authors and researchers are discussed. Firstly, accelerometers are mounted on the system and the vibrational signal data are collected, which needs to be further diagnosed. Figure 1 represents the equipment setup prepared by Case Western Reserve University (CWRU) which is generally used by many researchers to collect bearing vibration data. The signal data are processed using filters, denoisers and other techniques. The required features are extracted from the processed data, which quantitatively represented the faults in the bearings. The feature extraction techniques vary based on the signal data under the time domain, frequency domain, and time–frequency domain.

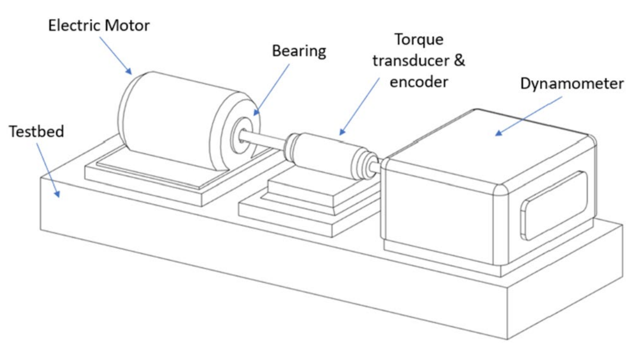

Fig. 1 CWRU equipment test setup for collecting bearing vibration data

In the time domain, the time waveforms were processed to extract certain features such as statistical parameters. These statistical parameters included mean–variance, skewness, Root Mean Square (RMS), kurtosis, and crest factor. Using time-domain data, identification of fault type was possible but the location of the fault couldn't be found. In the Frequency domain, the Fourier transforms or the various types of wavelet transforms were utilized for extracting features. Also, wavelet transforms could be applied to time-domain waveforms.

Xueli et al. [5] investigated the failure of the roller bearings used in wind turbines. The fault vibration signals from the roller bearings were decamped by Variational Mode Decomposition (VMD) method. Several parameters such as time and amplitude were used to decompose these signals and feature vector matrix was extracted. The obtained singular value was used bearing fault feature vectors. The rotational speed and sampling frequency used in the experiment were 260 rev/min and 2000 Hz respectively. The shaft misalignment was found to be the major reason for the bearing failure. The laser kit method was used to correct the shaft misalignment.

Xueli et al. [6] used intrinsic time-scale decomposition frequency spectrum for studying bearing fault diagnosis of wind turbine. Intrinsic time-scale decomposition frequency spectrum is used to analyze the bearing signal in this work. The acceleration vibrational signal was collected for four different types of bearing conditions, namely, bearing with no fault, bearing with outer fault, bearing with inner race fault and bearing with roller fault. In this method several proper rotation components were formed from the acceleration signal of the main bearing. Baseline extraction operator has been shown as € for signal X_t. The first decomposition of X_t is as follows

$$Xt = €X_t + (1 - €)Xt = L_t + H_t \quad \text{where } L_t = €X_t \text{ and } H_t = (1 - €)X_t. \tag{1}$$

L_t is the baseline signal and H_t is the proper rotation component. The first few rotational components were analyzed by the frequency spectrum. Further, the frequency amplitudes were added to get the frequency range. The experiments showed that this method was worked very effectively in finding the bearing faults in wind turbine.

Xueli et al. [7] used the Adaptive Local Iterative Filtering (ALIF) and approximate entropy methods for studying bearing fault diagnosis of wind turbine. The ALIF method was used to decompose original vibrational signals into a finite number of stationary components. One of the iterations of the ALIF method was capturing a single IMF (Intrinsic Mode Function) which is called the inner iteration. The updating step of the inner iteration was,

$$f_{n+1}(x) = f_n - \int_{-l_n(x)}^{l_n(x)} f_n(x+t) w_n(x,t) \mathrm{d}t \tag{2}$$

The components which had fault information were detected and sent to further analysis. The approximate entropy of these components was calculated. The calculated value was taken as a fault feature and as an input value to a fault classifier. Experiments showed that the proposed approximate entropy and the ALIF method worked effectively in finding the faults in the roller bearing of a wind turbine.

Patel et al. [8] used Harmonic Product Spectrum (HPS) method for analysing the roller element bearings (REBs). This method was different from other methods in the signal pre-processing step which was used in finding the fault raceway. Variational Mode Decomposition (VMD) method and classical bandpass filtering method as pre-processors were used to test the ability of the HPS to produce the desired result. The equations governing the dynamics of REB are written as

$$\begin{aligned} m_s \ddot{x}_s + c_s \dot{x}_s + k_s x_s + f_x &= 0 \\ m_s \ddot{y}_s + c_s \dot{y}_s + k_s y_s + f_y &= F_r \\ m_p \ddot{x}_p + c_p \dot{x}_p + k_p x_p - f_x &= 0 \end{aligned} \tag{3}$$

The total deformation of the jth rolling element, δ_j is given as

$$\delta_j = \left(x_s - x_p\right) \cos\left(\varphi_j\right) + \left(y_s - y_p\right) \sin\left(\varphi_j\right) - -cl$$

It was observed from the experiments that HPS produced better results when it is coupled with VMD, than that of bandpass filtering method. For parameter optimization of VMD, Non-dominated sorting particle swarm algorithm was used.

Xueli et al. [9] used the Vibrational Mode Decomposition (VMD) and permutation entropy methods for studying bearing fault diagnosis of wind turbine. VMD was used in this research to overcome issues of mode mixing and compensate for the limitations in empirical mode decomposition. To detect the randomness and kinetic mutation behaviour of a time series, permutation entropy was used. The level of complexity in turbines was very high so that the randomness and kinetic mutation behaviour of corresponding signals were displayed at different scales. So, for these highly complex vibration signals a multi-scale permutation entropy analysis was needed. The experiment was conducted on a sample with a slot width of 0.2 mm and slot depth of 0.3 mm and the sampling frequency was considered as 2000 Hz. The experiments proved the proposed method to be effective and provided new ideas for finding faults in roller bearings.

Xueli et al. [10] used the Vibrational mode decomposition energy distribution method for studying bearing fault diagnosis of wind turbine. Firstly, using the vibrational mode decomposition method, the original vibrational signal was converted into a finite number of stationary components. The decomposition is described below

$$\min_{u_k,\omega_k} \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) \times u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \tag{4}$$

Then for further analysis, the components which had major fault information were identified. The energy in different frequency bands of the vibration acceleration signals were observed to vary, when a rolling bearing fault occurred. Based on the K-nearest neighbour algorithm, the energy characteristic parameters could then be extracted from each component and taken as input parameters of the classifier. This helped in finding the type of fault that occurred in the roller bearing.

Xueli et al. [11] used the Adaptive Local Iterative filtering (ALIF) and singular value decomposition methods for studying bearing fault diagnosis of wind turbine. This method was used in conjunction to achieve the decomposition of the wind turbine's vibrational signal. Several stable components decomposed by the ALIF method, which contain major fault information is chosen to construct an initial feature vector matrix. The feature vectors of each bearing fault were taken from the singular value of the matrix. A system with 18-W output power, rotational speed of 260 rev/min and frequency of vibration signals as 2000 Hz were used in the experiment. The amplitude vs time graphs and time-domain waveform of roller bearing vibration signal with four states were used to achieve the desired results.

Yu Yang et al. [12] used improved intrinsic timescale decomposition de-noising and kriging-variable predictive model-based class discriminate for fault diagnosis of roller bearing. The noise signals were also been included in the vibrational signal of the bearing and it greatly influenced the accuracy of roller bearing fault diagnosis. So, it was very important to filter those noise signals from the vibration signals and this research work helped in achieving the desired signals sans noise. The improved intrinsic timescale decomposition method was used in de-noising the vibrational signal. This particular method extracted the fuzzy entropy as the fault feature of the roller bearing. Variable predictive model-based class discrimination was used to detect the fault bearing using pattern recognition. The experiments were conducted under a sampling frequency of 12,000 Hz. The experiment results proved that the proposed method was effective in detecting the fault in the bearing.

The possibility to fulfil the automatic recognition for roller bearing faults were some of the advantages provided by the above proposed method.

Patel et al. [13] used Daubechies wavelet for smoothing the signals. Through iterations 'Daubechies-6' wavelet was selected for noise removal in the collected vibrational data. Reconstruction filters were also used. A NJ-305 radial cylindrical roller bearing was placed at the far end position from motor. This whole process was done using regular defective bearings at inner race and outer race for functioning under a load of 0 N–25 N at different speeds. The signals were acquired for seven rotor speeds in the range of 600–3000 rpm. Also, time domain features like mean, kurtosis, RMS, crest factor and peak difference were extracted from decomposed time velocity signals. Mien Van et al. [14] worked on a three-phase performance improvement of the bearing fault diagnosis system which was carried out by introducing a new feature extraction technique based on a NonLocal Means of denoising (NLM). The Empirical Mode Decomposition (EMD) was used to process the time domain data. For selecting the feature, a hybrid technique was proposed by combining the Distance Evaluation Technique (DET) filter and Particle Swarm Optimisation (PSO) wrapper. Non-local means algorithm is as follows:

$$u(i) = \frac{1}{M(i)} \sum_{j \in \Omega_i} \omega(i,j) y(i) \tag{5}$$

$u(i)$ represents the NLM de-noised values at the sample i and $M(i) = \sum_{j\in\Omega_i} \omega(i,j)$ is a normalisation constant. Jianpeng Ma et al. proposed a composite ensemble intrinsic time scale decomposition with adaptive noise method (CEITDAN) which was used in decomposing the signal at different scales. To analyze the complexity of the vibrational signal they used refined composite multi-scale approximate entropy method.

Ke li et al. [2] proposed a fault diagnosis method based on Adaptive Statistic Test Filter (ASTF) and Diagnostic Bayesian Network (DBN). To evaluate the performance of STF, a function I_{pq} is defined. Smaller the value of I_{pq} better the STF will be.

$$I_{pq} = \frac{\sum_{i=1}^{K} \log\left(\frac{q_i}{q_{i*}}\right)}{K} + \frac{\sum_{i=1}^{K} \log\left(\frac{p_i}{p_{i*}}\right)}{K} \tag{6}$$

To obtain weak fault features under background noise, an Adaptive Statistic Test Filter was used. This was used to evaluate the similarity between original and noise signal in the frequency domain. A three-layer DBN was used to identify the condition of bearing based on the Bayesian Belief Network (BBN) theory. This experiment was carried out at 800 rpm and 1.5 kN load was applied on the system and the sampling frequency was 50 kHz. Four bearing states—normal, outer-race defect, inner-race defect, roller defect were considered.

The Continuous wavelet transform method was used by Laohu yuan et al. [15] to obtain the signal information. To process the signal, an optimal Wavelet Basis Function (WBT) which is based on the Gaussian radial basis function was chosen. For this experiment, seven load conditions were considered from 25 to 300 pounds. Wathiq Abed et al. [16] used Discrete wavelet transform (DWT) method for the feature extraction. Daubechies four (db4) with five-layer decomposition method was used to identify the severity of bearing defects. Also, Orthogonal Fuzzy Neighbourhood Discriminant (OFND) features were extracted. This experiment was carried out under 4 different rpms in between 300 and 1200 and under various loading conditions like no load, 25%, 50%, full of rated load to study the effects on bearing faults.

In most of the works, the rotational speed used was around 300 rpm and some of them with a speed greater than 1500 rpm. Sampling frequency of most of the experiments was observed to be 2000 Hz and in some of them frequency went much beyond 10 kHz.

Oil–Air Lubrication and Thermocouple Analysis

Roller bearings are widely used in many applications such as rolling mills, paper machines, etc., which operate at low-speeds and high loads. These bearings can also be used for high-speed applications. For ensuring the safe operation of high-speed locomotive, rolling bearing is the key component. The double-row tapered roller bearings in high-speed locomotives are also one of the most vulnerable parts. This heavily loaded equipment is lubricated with lubricating greases. The frictional heat at high rotational speed induces temperature rise in the bearing and affects its service. Hence, it is very important to accurately estimate the temperature increase of roller bearings through thermal analysis.

Zhou Chang et al. compiled a list of all possible modes of contamination-related mechanical failure [17]. The roughness, hardness, size and kind of contamination are frequently linked to the failure mode of failed bearings. Contaminants can produce abrasion, indentation, burn-up, corrosion, and a variety of other failure modes, each with its own set of characteristics. Fatigue is induced by the action of alternating stress on the bearing raceway. The abrasion rate is proportional to the normal load and also the load and wear on the inner ring is bigger than that acting on the outer ring. Due to a shortage of lubricating oil, the sliding friction increased, thereby raising the temperature. The bearing then burns up due to the high temperature. Indentation may occur if larger particles penetrate the bearing raceway. Ball failure mode analysis reveals that the ball was subjected to alternate stresses, resulting in fatigue spalling. Through Cage failure analysis, the breakage of the cage was found to occur when the load between the cage and the ball was too high. Bearing seizure happens when the cage load is too excessive for fracture. Also, overheating can produce bearing seizure. The analysis using energy-dispersive X-ray spectroscopy was also carried out. The findings revealed the existence of four new elements in the abrasion-affected bearings, namely, O, Al, P, and Ni, with weight percentages of 4.32, 0.67, 0.48, and 4.68 wt %, respectively, indicating that new particles had polluted the oil layer. The abrasion failure occurs when the particle hardness is extremely high.

Li Liquana et al. studied the performance of two lubricating system, namely, oil–air lubrication and oil lubrication. A friction-abrasion testing equipment was used to evaluate the effect of oil–air lubrication on classic sliding bearings [18]. The friction moment and temperature increase were the two parameters considered for comparison between the two lubricating systems under similar conditions. They were studied for different loads, but, with same rotating speed level. In this case, an M2000-A type friction and wear testing machine was used. The rotor speed had two shifts, 210 rpm and 420 rpm, with a load range of 0–2000 N. Sliding bearings with oil holes and temperature blind holes were constructed with $ZCuZn_{40}Mn_2$. The 45-steel tile seat had an oil tank, an oil hole, and two temperature measurement holes. Both oil lubrication and oil–air lubrication were adopted for this process. The results showed that when the rotating speed and oil supply were both set to 210 rpm and 1.4 L/h, the friction moment of the bearing with oil lubrication increased significantly after the load of 900 N. In the case of oil–air lubrication, a significant increase was observed on the friction moment after 1500 N with the rotating speed, oil supply, and air pressure were 210 rpm, 30 ml/h, and 0.25 MPa, respectively. With the identical experimental conditions, the temperature rise in the oil–air lubrication system was found to be substantially lower than that of oil lubrication system.

Bei Yan et al. researched on jet lubrication which was becoming more popular in high-speed rolling bearings as a cost-effective lubrication solution that allows for precise control on the amount of lubricating oil and time interval [19]. *Oil–air jet lubrication*, in particular, is presently the dominant lubrication method and is widely used in high-speed and high-precision ball bearings as a highly efficient and low-pollution lubrication technology. With diverse oil–air supply techniques, high precision models were created to explore airflow pattern and lubrication performance inside bearing cavity. The oil–air interface was tracked using the Level-Set function and the Volume of Fluid (VOF) approach, and the migration and diffusion process of oil droplets inside the bearing cavity was determined. The rise in bearing temperature was evaluated and compared with outer ring and lateral oil–air lubrication methods at different rotation speeds using a high-speed oil–air lubrication test equipment. Finally, the synergistic analysis was used in conjunction with the internal flow and temperature field distribution, to estimate the lubricant flow and heat dissipation performance of the bearing internal cavity and other important locations. The oil–air jet nozzle positions have a significant impact on the airflow pattern and heat transmission inside the bearing cavity. The airflow from the nozzle was less affected by bearing components in the lateral supply approach, resulting in lower flow resistance and improved heat dissipation inside the bearing cavity. When lubricating oil was provided by an outer ring nozzle, rather than a lateral oil–air supply technique, the oil gets concentrated in the inner and outer raceways, as well as the cage pocket, and the utilization rate of the oil was observed to be higher.

Miaomiao Li et al. studied on the creation and accumulation of a substantial amount of frictional heat that can cause the bearing temperature to rise and reach dangerous levels, significantly reducing bearing life [20]. Oil–air lubrication technique leads to considerable reduction in bearing temperature growth, through accurate control of oil–air parameters, providing high lubrication and thereby, obtaining good cooling efficiency. To study the flow field and temperature field, this work provided a Computational Fluid Dynamics (CFD) steady-state analytical model of oil–air lubricated angular-contact ball bearings based on fluid–solid conjugate heat transfer. To ensure the correctness of the simulation results, a temperature rise test of oil–air-lubricated angular-contact ball bearings was performed. The impact of lubrication settings, operating conditions, and rolling element materials on the temperature rise characteristics of oil–air-lubricated angular-contact ball bearings were investigated using a fluid–solid conjugate heat transfer steady-state analytical model. When it comes to the impacts of oil–air lubrication parameters, the temperature rise of each area of the bearing reduces, as the air pressure rises. The inner ring's temperature rise is substantially bigger than the outer rings. With the following working conditions, an axial load of 600 N, radial load of 600 N, a compressed air pressure of 0.2 MPa, an oil supply of 1 ml/h and the inner ring speeds of 3000, 6000, or 9000 rev/min, the temperature increase for every part of the ceramic ball bearing was observed to be substantially lower than the steel ball bearing, and with increase in speed, the greater was the difference in temperature between the two.

Lorenz1 et al. [21] used a dry asperity contact model and Reynolds-averaged equation with laminar flow conditions for the analysis of hydrodynamic bearings. The equation for an average temperature distribution was as follows:

$$T_m(x, z, t) = \frac{1}{h}\int_0^h T(x, yz, t)\mathrm{d}y \tag{7}$$

$$C_p\frac{\partial(aT_m)}{\partial x} + C_p\frac{\partial(bT_m)}{\partial z} + C_p\frac{\partial(cT_m)}{\partial t} + \mathrm{d}T_m = e \tag{8}$$

For the temperature distribution in the lubricant and the bearing structures, a new model had been developed adding to the previous model. This model includes the thermal interface conditions between these domains, which takes into account the asperity energy source. It is used for the estimation of temperature in supply zones. This model was applied for carrying out the sensitivity analysis for oils with different viscosity index improvers, in the main bearing of a four-cylinder inline diesel engine. The results of the conducted experiments showed almost similar accuracy of the two-dimensional approach compared to the equivalent three-dimensional case.

Hongqi Li et al. [22] worked on the analysis of bearing configuration effects on high speed spindles using an integrated dynamic thermo-mechanical spindle model. A comprehensive bearing dynamic model, a shaft dynamic model and a thermal model were together integrated to be called as Dynamic thermo-mechanical model. Heat generation and thermal expansion of the whole system on the bearing configuration was evaluated by coupling the thermal model with the spindle dynamic model. To model more general cases of bearing configurations, it was important to consider a pertinent mapping between bearing stiffness and shaft stiffness matrices. The new thermo-mechanical model considers both these factors. A Mazak spindle with a speed of 6000 rev/min and a mass of 3.25 kg was used for the simulation.

Ru Chen et al. [23] worked on Thermal Terahertz Analysis (TTA) for detecting the oil bearing features in a desert reservoir. To measure the pyrolysis products of sands collected from the shallow ground, it was beneficial as they used a method called Thermal terahertz analysis, which was sensitive to the difference of organic matter and minerals. For the 2.3% rate of mass change during the pyrolysis stage of organic matter from ~ 300 to ~ 700 °C, THz parameter showed 20.4% rate of change. A depth of 1.5 m in the desert oil field was maintained between the surface and the collection location. The size of sand particles varied from 50 to 300 micro meters. The research showed that carbonates had smaller absorption in the THz range than the oxides.

Fangbo et al. [24] worked on Transient thermal analysis of grease-lubricated Spherical Roller Bearings (SRB). For accurately calculating the heat generation rate of grease-lubricated roller bearings a mathematical model was established based on the local heat source analysis approach. Using a thermal network method, the transient thermal model was developed for a grease-lubricated SRB-shaft-bearing housing system. The developed system was numerically solved and the results supported the experimental results. The relationship between elastic deformation and load for roller-race waypoint contact was established as,

$$\frac{\delta}{Rx} = 1.7138\, k^{-0.2743} W_{\mathrm{PC}}^{2/3} \tag{9}$$

The rotating speed of the inner ring was 1500 rpm. The results showed that the temperature rises with larger rotating speeds, radial load, and grease filling ratios. It was also observed that higher the base oil viscosity, higher was the SRBs temperature.

Shaoyu et al. [25] investigated on Thermal turbulent lubrication analysis of rough surface journal bearing with journal misalignment. The Hashimoto turbulent lubrication model and the Patir–Cheng laminar flow lubrication model when combined, presents the generalized turbulent lubrication equation for isotropic rough surface bearings. Sommerfeld's number is,

$$S = \frac{\mu_0 \mathrm{LUR}^2}{\pi \mathrm{WC}^2},\ C = c + K_{\mathrm{sm}} \tag{10}$$

The generalized turbulent lubrication equation and energy equation could be solved using the finite difference method. Under the influence of surface roughness and journal misalignment, variations for turbulent lubrication performance of journal bearing with the nominal eccentricity ratio and nominal average Reynolds number could be obtained. The eccentricity ratio and the average Reynold's number are given as,

$$\varepsilon = \frac{e}{C},\ \mathrm{Re}^* = \frac{\rho \mathrm{UC}}{\mu_0} \tag{11}$$

The dimensionless maximum film pressure, dimensionless load capacity and dimensionless misalignment moment of the bearing were increased when the dimensionless surface roughness height of the bearing and the journal increases or when the degree of misalignment was increased.

Surajkumar et al. [26] investigated on theoretical and experimental studies to predict defects in spherical roller bearings using dimensional theory. Rolling element bearings are important items in condition-based maintenance because they enable frictionless force transmission between the mechanical components of high production volume systems. With the use of dimensional analysis with Buckingham's pi theorem (BPT), by considering significant geometric, operating, and thermal parameters of the system, a new approach was demonstrated to develop a dynamic model for vibration response of spherical roller bearings. The results from the developed model were verified with experiments performed on the developed test rig under diverse operating conditions and the results showed that the approach was simple and reliable.

Shaik Mujeebur et al. [27] worked on structural and thermal Analysis on the Tapered-Roller Bearing. Generally, hot-box detectors were used to detect any damaged bearings in the rail road industry. In general wayside hot-box detectors raised an alarm if the temperature was greater than 105 °C. Taper roller bearings were subjected to lot of cyclic loads, so it was suggested to increase the temperature by 15 °C and therefore, the goal of the research was to increase the Hot Box Detector temperature. To find out the temperature distribution between the cup and roller surface of the bearing, finite element analysis was carried out.

Siyuan Ai et al. [28] worked on temperature rise of double-row tapered roller bearings considering the thermal network. The thermal characteristics under working condition are one of the main factors that affect the service reliability of double-row tapered roller bearing in high-speed applications like railways. For bearing's structure design and operation monitoring, it was important to research on the heat generation and the temperature field. The combination of local thermal approach and elastohydrodynamic lubrication (EHL) theory were used for heat generation model for both raceway and rib of railway bearings. To analyze bearing's temperature field distribution and its influence factors, the finite element method was employed. With increase in radial force and speed, the heat generation of rib and raceway increased. Heat generation of rib was much lesser than that of raceway.

Yan Ke et al. [29] investigated on theoretical and experimental investigation on the thermal characteristics of double-row tapered roller bearings of high speed locomotive. The double-row tapered roller bearing, lubricated with grease was commonly used in high-speed railway and based on generalized Ohm's law, the thermal network model was developed for these bearings. Power loss due to friction is,

$$P = M \cdot \omega_i = M \cdot \frac{2\pi n_i}{60} \tag{12}$$

A quasi-static model was used for obtaining the load distribution and kinematic parameters in the bearing. At different speeds, filling ratios and roller large end radius, the temperature of bearing was investigated. The heat convection coefficient between the outer surface of house and air is taken as:

$$\alpha = \begin{cases} 0.3(T - T_a)^{0.25} & \text{Natural heat convection} \\ 0.3\frac{k_a}{D_h}R_e^{0.57} & \text{Forced heat convection} \end{cases} \tag{13}$$

The experimental conditions are the speeds of high-speed railway car 250 km/h, 350 km/h and 500 km/h corresponding to the rotational speeds of double-row tapered roller bearing 1543 r/min, 2160 r/min and 3086 r/min, respectively. A significant temperature rise was observed, especially at roller large end/flange contacts corresponding to high rotating speed and large filling grease ratio.

Yigit et al. [30] varied the quality of the grease used in bearings for wind turbine application and investigated the effects on the fatigue life of the main bearing. Due to uncertainties associated with degradation mechanism and variations in the grease batch quality, monitoring the grease condition through predictive models would be a daunting task. Variable grease quality caused discrepancies in the grease life predictions which lead to inaccurate bearing fatigue life predictions. To solve the above problem, a new approach was adopted in this research called hybrid physics-informed neural network model. For bearing fatigue damage accumulation embedded as a recurrent neural network cell, a hybrid model was constructed. In the hybrid cell, reduced-order physics models were used for bearing fatigue damage accumulation. To quantify the grease quality variation, a two-step probabilistic approach was used. In the first step, to know the grease degradation when the quality was the median of the distribution, hybrid model was used and in the second step, the median predictor from the first step was used to track the quantiles of the quality distribution.

Junning Li et al. [31] worked on the thermal distribution characteristics of High-Speed and Light-Load Rolling Bearing considering skidding. The effect on thermal distribution and reliability was high if there existed skidding in any bearing. So, a theoretical model on high speed and light load rolling bearings (HSLLRBs) was considered to get the friction power loss distribution. Using finite element method (FEM), transient and steady temperature field distribution of the bearing was obtained. This experiment was carried out at 18,000 rpm and the radial load acting on the shaft was 2000 N. The effect of slip ratio on friction power loss at different parts of the bearing was obtained. The results showed that center of the inner ring race had the highest temperature of 114.7 °C and the outer surface of the cage had the lowest temperature of 81.7 °C. Also the temperatures of the outer and inner ring race increased with increase in slip ratio and the cage temperature decreased as the slip ratio increased. Senthil Kumaran et al. [32] investigated the effect on stress and thermal analysis of tapered roller bearing. Initially a 3D model of tapered roller bearing was made and numerous tests were carried out on the virtual work piece. At the inner ring, a radial load of 3923 N was applied and on the outer ring of the bearing a load of 5000 N was applied. The rpm was taken as 2000. The output showed that the wear was mainly because of the wastage of the metal material and the dirt in the lubricant. Using grease along with silicon as lubricant, the temperature was brought down from 100 to 60 °C under 2 s in continuous work process.

Table 1 Methods used in research works at different loading conditions for bearing fault analysis

S. No	Authors	Limitations		Method	Temperature	
		Loads(N)	Speed (rpm)		Min. Temp (°C)	Max. Temp (°C)
1	Norbert Lorenz et al. [21]	–	3000–4000	Reynolds-averaged approach	117.5	172.5
2	Hongqi Li, Yung C. Shin [22]	–	6000–40,000	The dynamic thermo-mechanical model	–	38
3	Ru Chen et al. [23]	–	–	Thermal terahertz analysis	300	700
4	Fangbo Ma et al. [24]	12	1500	Local heat source analysis	20	130
5	Shaoyu Zhu et al. [25]	–	–	The finite difference method	40	120
6	Shaik Mujeebur Rehman et al. [27]	159 kN	–	Finite Element Analysis	–	56.135
7	Siyuan Ai et al. [28]	–	1543, 2160	Thermal network model	40	72
8	Yan Ke et al. [29]	70.6 kN, 14.2 kN	462–1385	Heat generation model	42.9	52
9	Junning Li et al. [31]	2000	18,000	Finite element method	81.7	114.7
10	Senthil Kumaran et al. [32]	3923–5000	2000	ANSYS	60	100
11	Juan Xu et al. [33]	50 kN	–	Finite element method	–	80

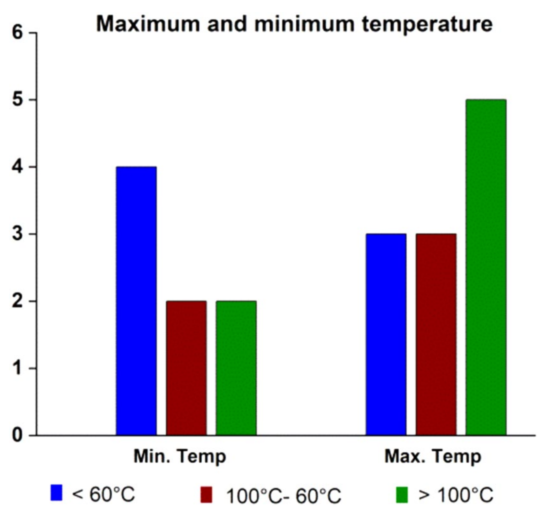

Fig. 2 The number of experiments with maximum and minimum temperature ranges

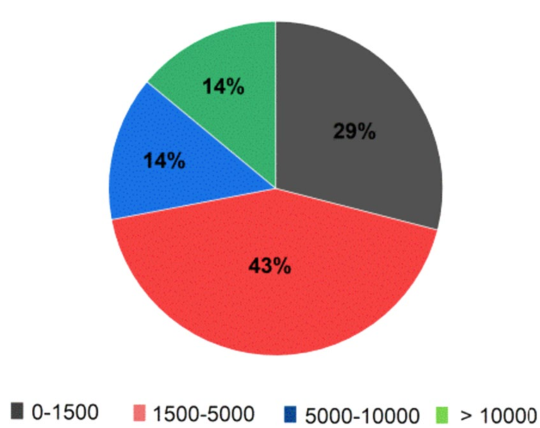

Fig. 3 The number of experiments with different speed ranges

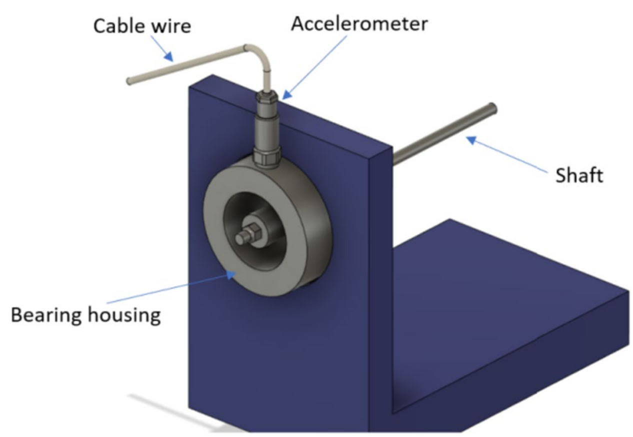

Fig. 4 Sensor mounting on top of bearing housing

Juan Xu et al. [33] studied on calculation and finite element analysis of the temperature field for high-speed rail bearing based on vibrational characteristics. A double row tapered roller bearing was researched to study the steady temperature field and its relationship with the critical speed. A radial force of 50 kN was applied on each bearing. A highest temperature of 80 °C was obtained at the contact area. The temperature at the outer raceway was found to be 65 °C. Also, the effect of coupling variation on the critical speed was higher when compared with the effect of elastic modulus.

Table 1 summarizes the methods used by the researchers for analysing the roller bearings. Out of all the methods used, Thermal network model and finite element analysis stand out and were most commonly used. The maximum temperature attained in most of the experiments was above

100 °C. The speed and the load used in the research works are mainly above 2000 rpm and above 50 kN respectively.

Figure 2 shows the number of experiments with maximum and minimum temperature ranges.

The Fig. 3 shows the number of experiments with different speed ranges.

Mounting of Sensors

Bearing health monitoring, which is considered a critical component of rotating machinery, is believed to aid in the prevention of machine breakdown and ensure machine availability. Both the signal processing techniques and the location of the sensors for fault characteristic extraction influence the integrity and efficiency of measurement systems for monitoring the status of the bearing. Figure 4 represents sensor mounting on top of bearing housing at 90 degrees. The experiments were carried out with a variety of bearing settings, operating circumstances and sensor placement sites.

Deepam Goyal et al. [34] used a non-contact optimal sensor placement (NC-OSP) methodology to acquire high-quality information related to dynamic features of a machine. The shaft speed was the most effective input parameter to control FFT vibration amplitude of characteristic frequency and RMS value of time domain, followed by the load on shaft. It was also recommended to utilize Response Surface Methodology (RSM) for tracing optimal non-contact sensor location.

Robert X et al. [35] measured vibrations of two custom-designed bearing testbeds through numerical simulation using a group of sensors. The Effective Independence (EFI) method was adopted for optimizing the sensor placements based on Fisher Information Matrix (FIM). The EFI-based ranking method for sensor locations gives a feasible approach to work out a systematic sensor placement strategy. The iterative location ranking process was conducted based on the accuracy of a structural model which affects the performance of individual locations. The results showed that placing sensors close to the selected component would increase the signal-to-noise ratio. The precise sensor positions were established to focus on the dynamics of the structure to be supervised.

Changdong Wang used ALSCN for effectively extracting features directly from high-dimensional source data [36] With the addition of two upgraded multi-scale modules, adaptive long sequence convolutional network (ALSCN) could not only extract significant features from noisy signals more efficiently, but it could also prevent losing key information due to constant down sampling. ALSCN-based defect diagnosis method eliminated the need for manual feature extraction and also modified hyperparameters adaptively for various application scenarios. In addition, the study developed two improved multi-scale modules to significantly sustain spatial correlation on longer signals and compensate for the loss of detailed information due to severe noise. This allowed ALSCN to diagnose longer time series in the presence of high noise in actual engineering applications. On the four data sets of the Case Western Research University (CWRU), the average accuracy of the ALSCN improved as compared with the traditional methods of Support Vector Machine (SVM) and deep learning methods like Convolutional Neural Network (CNN), Deep Belief Network (DBN), Back Propagation Neural Network (BPNN), and Recurrent Neural Network (RNN).

Lokesh A. Gupta used a permanent neodymium magnet in the shape of a ring and a Hall Effect sensor [37]. The sensor can monitor bearing temperature wirelessly from a distance of 40.5 mm based on the temperature-induced variations in a magnetic field. A temperature-sensitive permanent magnet was attached to the inner race of the bearing, allowing the temperature of the bearing to modulate the produced magnetic field. To change the distance between the magnet and the Hall Effect sensor, the sensor was placed on a Z-axis apparatus. The presented magnet and Hall Effect sensor were placed on a bearing test rig. A thermocouple was also installed near the bearing outer race to accurately measure its temperature.

Shlomi Konforty et al. [38] investigated the feasibility of using an optical fibre sensor of the Fibre Bragg Grating (FBG) type, which detects strain and temperature changes, for bearing diagnostics. This was specially chosen because, weak bearing signals cannot be detected with a low signal-to-noise ratio in the presence of lot of noise. A FBG sensor was used to measure strain. There were two implementations investigated: a MEMS accelerometer placed on the bearing outer race and strain measurement using an optical fibre on the bearing housing. Despite the currently imperfect sensor features, the closer sensors provided better identification of defects in both methods.

Safizadeh et al. proposed a method for detecting bearing faults based on the combination of two primary sensors: an accelerometer and a load cell [39]. A unique condition-based monitoring (CBM) system with six modules was recommended: sensing, signal processing, extraction of features, classifying, high-level fusion, and decision making. The *K*-Nearest Neighbour (KNN) classifier was used to identify the condition of the ball bearing based on vibration and load signals. A high-level sensor fusion was used to obtain information that a single sensor would not provide. The situation assessment performed during the classifier training process helped in devising a relationship between bearing condition and sensor performance. Finally, a logical programme was used to decide about the condition of the ball bearing. The findings suggest that the load cell was capable of effectively distinguishing the healthy and defective ball bearings.

Henrique D. M. de Azevedo installed accelero- meters on the main components of a wind turbine and a vibration monitoring technique was carried out using signal processing methods like Fourier transform and envelope analysis with Hilbert transform [40]. This was performed before and after the replacement of bearing. The (accelerometer and tachometer) were firmly attached to the surface being tested and linked to a data logger, which in turn was linked to a switch. The rotor assembly, main shaft, and first stage of the gearbox were classified as low frequency, whereas the second and third stages of the gearbox and generator were classified as high frequency of a wind turbine. The analyses were carried out by applying three standard analyses: temporal variations of vibrating signals, spectrum analyses using fast Fourier transforms, and envelope analysis using Hilbert transformation.

O'lmasov Ahadjon Akramjon scrutinized on innovative technologies for evaluating problems in the main equipment of a thermal power plant using shaft sensors that forecast static and dynamic shafting movements during the start-up and stationary operation of the turbine unit [41]. The geometry of the rotors and bearings, as well as the conditions of their assembly, bearing alignment, compensatory alignment of the rotors by half couplings, and calculated data of the ascent of the rotor necks were all required to obtain a static line of the shaft. Vibration data from all sensors, namely, sensors of relative vibration of the shaft, and sensors of absolute vibration of bearings were used to generate a dynamic line of the shaft to forecast radial impacts in the end seals and in the flow portion. The proposed method was based on the usage of four sensors for relative shaft displacement and a set of sensors for absolute support movement. The comprehensive method allowed to analyse alternating voltages in the components of the shaft line at known relative movements.

To build and deploy an effective condition monitoring system, careful selection and placement of sensors are critical. A thorough statistical investigation of several sensor placement strategies for high-quality sensing was reported in this research using response surface methodology technique. The core purpose of the study was to discover the most possible and optimal sensor placements to ensure efficacy of the fault diagnosis and measurement quality.

Neural Networks for Fault Diagnosis

For fault diagnosis of bearings, different types of methods can be used and they can be roughly classified into two categories. One category depends on the expert knowledge to analyze the faults which are known as model-based fault diagnosis methods. This requires a very high expertise in that field and is limited to certain extent. The second category is based on series of data. To extract features from this big data, neural networks are used. There are various types of neural networks, the most commonly used are Convolutional neural network (CNN), Recurrent neural network (RNN), Deep neural network (DNN), Bayesian neural network (BNN) and probabilistic neural network (PNN). CNN is the widely used neural network these days with some modifications to it. CNN uses convolution and pooling layers to extract features from the data.

Xiaochen Zhang et al. proposed a multiscale convolutional neural network and gated recurrent unit network with attention mechanism (MCNN-AGRU) to detect early-stage faults in rolling bearings [42]. CNN is a neural network which has convolution calculation and depth structure. The data features were extracted using Convolution and pooling, which decreased the error caused by artificial feature. The attention mechanism was a resource allocation mechanism, which makes the model easier to learn the long-distance interdependence in the sequence. The fault data were collected at four different conditions namely: normal state (N), the inner ring failure, the outer ring failure, and the rolling elements failure. Digital data was collected at 12,000 samples per second. A radial load of 6000 lbs. was applied to the shaft and bearing at the speed of 2000 rev/min through a spring mechanism to accelerate bearing aging. The work concludes that fault diagnosis by MCNN-AGRU was observed to be simple and intelligent to that of traditional methods which requires more experience and knowledge.

Martin Hemmer et al. proposed a Transfer Learning through a Pretrained Convolutional Neural Network to classify faults in axial and radial bearings [43]. The vibration signals were converted into images as pixels or a matrix before feeding them to the AlexNet architecture. To detect specific features that were present in the input, these images go through several convolutional layers, which act as learnable filters. The processes carried out in the above section were CNN, SVM, and SAE-SVM. The feature extraction was done directly from the pretrained CNN and SVM was choosen for classification. This was considered as the optimum option for detecting faults in roller bearings in terms of robustness, easy implementation, and computational burden.

Renwang Song et al. [44], stated that the difficulty in anticipating rotating machinery defects is due to incomplete diagnostic information, insufficient multisource sensor information, and weak diagnosis models. So, multiple domains and heterogeneous information entropy fusion approach based on bearing defect diagnostic optimization to solve these constraints was suggested. The spatiotemporal technique employed a multiscale domain fusion strategy based on heterogeneous (HSMSF) to extract feature fusion strategies, and multichannel processes using convolutional neural networks to analyze the characteristics of bearing defect features in vibration signals. High-quality features were integrated after mapping several quality parameters, and the adaptive entropy weighted fusion approach was utilized to analyze and make judgements on sensor data. Adaptive optimization utilizing the chaotic elitist modified sparrow search algorithm (CEI-SSA) was used to identify 19 critical model parameters required for HSMSF creation, and a self-learning diagnostic model suited for numerous detection locations was built. These approaches were tested on two widely used reference datasets, CWRU and Intermediate-Speed Shaft (IMS).

A new CNN technique based on LeNet-5 was presented for defect diagnosis, which recovers features from converted 2-D images and avoids the effect of handcrafted features [45]. The proposed method was tested on three well-known datasets: motor bearings, self-priming centrifugal pumps, and axial piston hydraulic pumps. The results were compared with traditional methods such as adaptive deep CNN, sparse filter, deep belief network, and support vector machine. According to the findings, the proposed CNN-based data-driven fault diagnosis solution exceeds the competition.

Daoguang Yang et al. stated that the Deep learning algorithms now in use were often based on single signal properties, resulting in the loss of some information or insufficient utilization of the signal's information [46]. In this analysis, four different datasets were created from raw vibration signal as the input data for CNN models using two different signal processing methods, including Fast Fourier Transform (FFT), and Short-Time Fourier Transform (STFT). Soft Pool and Mish activation functions were added to normal convolutional neural networks to boost feature extraction ability. Second, raw vibration data were translated into three different sorts of signals, which were then used to train a sequence of CNNs to produce the findings. Finally, an explainable fuzzy fusion technique was applied to rotating machinery defect diagnosis to improve diagnostic performance, and the Shapley index was used to explain the classifier contributions and interactions index among these classifiers. The results reveal that, despite taking longer, the modified CNN outperformed the regular CNN in a noisy environment.

Gang Chen et al. [47] proposed a frequency temporal logic to get the frequency properties of fault signals. Along with Bayesian Neural Networks (BNN), Bayesian optimization method was combined to get the structure and parameters of the FFT described. This experiment was carried out at 1800 rpm at a sampling rate of 12 kHz. Four types of bearings were tested i.e., inner race fault, outer race fault, rolling element fault, normal state bearing. The results showed that the proposed method was able to solve the problem with minimum computation cost.

To improve the feature extraction process of a motor bearing, Probabilistic Neural Network (PNN) method was proposed by Fanchao Min et al. [48]. In this experiment to extract the features from the vibrational signal, Wavelet Packet Decomposition (WPD) method was used with an improved eigen value extraction method. The sampling frequency was 12 kHz, and the motor speed was 1797 rpm. Four types of faults are simulated including normal, inner ring fault, outer ring fault, and rolling element fault. The proposed method was found to be feasible with good recognition effect. Also rapid fault detection was possible in short period of time with almost 98% accuracy.

Wentao Zhang et al. [49] proposed a hybrid method by combining a Convolutional neural network and error fusion of multiple sparse auto-encoders. The encoders were used to collect the feature information and then a trend curve was obtained to represent the bearing condition. A threshold line was plotted to identify the early fault by computing the square prediction error (SPE). In this experiment, two operating conditions were considered. One at 2250 rpm and 11 kN radial load and the other at 2400 rpm and 10 kN radial load. The sampling rate of the data was 25.6 kHz with an interval of 1 min and the duration of sampling was 1.28 s. It was demonstrated that the proposed method could predict the failure more effectively when compared to other advanced prediction methods.

Davor Kolar et al. [50] used Convolutional Neural Network (CNN) along with Automatic Hyper-Parameters tuning by Bayesian Optimization method for Intelligent fault diagnosis of rotary machinery. In this work, high definition 1-D data was acquired from a three axes accelerometer signal, and this data were converted into deep learning layers. Four different machine state conditions were considered: normal, unbalanced, eccentric, and cocked state at 1000 rpm and 1500 rpm. The sampling frequency was taken as 51.2 kHz. Two bearings with inner race, and outer race faults were analyzed. This method showed a classification accuracy of 99.94%.

Md Junayed Hasan et al. developed an autonomous diagnostic system that combines signal-to-image transformation techniques for multi-domain information with a convolutional neural network (CNN)-aided multitask learning (MTL) to address challenges such as extracting non-linear and non-stationary vibrations of fault bearings at variable speeds and load conditions [51]. A composite color image was formed by combining information from many domains, such as the raw time-domain signal, the spectrum of the time-domain signal, and the envelope spectrum of the time–frequency analysis, to handle changeable operating conditions. Even with varying speeds and loads, this 2-D composite image, known as Multi-Domain Fusion-Based Vibration Imaging (MDFVI), seemed to be particularly effective at generating a unique pattern. The proposed

MTL-based CNN architecture then uses these MDFVI images to discover problems in variable speed and health conditions at the same time. Two benchmark datasets from the bearing experiment were used to test the suggested technique. The proposed strategy outperforms state-of-the-arts in both datasets, according to the results. MDFVI, a two-dimensional composite picture approach, was particularly successful at establishing a unique pattern independent envelope spectrum. These MDFVI images were then sent into the proposed MTL-based CNN architecture, which was capable of accurately detecting defects in both changing speed and health states at the same time.

Lifan Kong et al. developed a multi-scale weight distribution convolutional neural network model to address the problem of the current convolutional neural network model which cannot adaptively acquire more effective features [52]. The feature extraction layer, multi-scale feature connection layer, and classification layer make up the model. In the feature extraction layer, the weight distribution mechanism was introduced. Experiments were conducted using the Case Western Reserve University (CWRU) data set to evaluate the model's viability, and the results showed that the model could efficiently extract features under different operating settings and had high fault recognition skills. The weight distribution strategy allows the model to extract more useful feature information while also reducing the weight of invalid features. It increases the accuracy and consistency of fault detection.

Feng He, Qing Ye proposed a new method of bearing fault diagnosis based on wavelet packet transform and convolutional neural network optimized by simulated annealing algorithm. Start-import vibration signal data was processed through Wavelet packet transform than formulated into spectrogram which is trained in CNN that helps in detecting bearing fault [53]. The method used Wavelet Packet Transform (WPT) to preprocess the original vibration data to construct a spectrogram, which served as the convolutional neural network's training data. The ideal settings were then found using the simulated degrading algorithm, which replaced the manual parameter change process. This proposed method featured a simpler parameter setting and a greater accuracy rate, according to the final results. The convolutional neural network's volume was quite small, making it easy to transplant in the industrial field. It was easier to achieve cross-platform transplantation while maintaining a particular accuracy rate as compared to large-scale networks.

Ugur Ceylan et al. [54] used a Siamese network architecture based on the inception time deep Convolutional Neural Network (CNN). The Siamese element of the network allowed the recurrent usage of existing data to generate a similarity metric for two different time frames. The suggested model was validated using NASA's C-MAPSS dataset for turbofan engines. It presents a Siamese network with temporal data processing capabilities for fault diagnostic classification and regression in the absence of a large amount of failure data. The traditional deep learning models struggle to view a window-based similarity score with limited sets of training samples. However, the suggested method allows for numerous usages of the data. The temporal processing was possible with the Inception Time network. The outcomes showed that the model could be employed in defect diagnosis and may deliver satisfying prediction results with less data while performing similarly to state-of-the-art Remaining Useful Life (RUL) prediction approaches.

To identify the defective components and damage in the bearing a Deep Convolutional Neural Network (DCNN) method was proposed by Anil Kumar et al. [55] using continuous wavelet transform, 2D greyscale images of time–frequency representation were processed from vibration signals. Features were extracted from images through convolution and pooling operation layers. Then trained 2D grey images were applied to DCNN so that the defect severity assessment can be accurately carried out.

Mohammadkazem Sadoughi et al. [56] stated that the most of the approaches focus on fault diagnosis of a single bearing but in reality, multiple bearings will be present in rotating machinery. So, to solve this problem a method was described which was stated as physics-based convolutional neural network (PCNN). To extract data from raw sensor signals, spectral kurtosis and envelope analysis were used. After training the model, multiple physics layers were added to the CNN model. To reduce the number of training parameters in the model, data-driven kernels were replaced with the physics-based kernels which thereby reduces the risk of over-fitting.

Seokju Oh et al. [57] created a dataset by adding noise to resemble the noisy manufacturing installations in the field and then denoising autoencoder (DAE) was used to accurately inspect the bearing defects. Complex features were extracted effectively from the signals using the multi-scale convolution neural network (MS-CNN) method. The results revealed that the proposed DAE method needs to be improved to get a more effective noise reduction.

Jiangquan Zhang et al. [58] researched on a method for converting two-dimensional images from raw inputs. This approach can extract the features of transformed two-dimensional images without relying on expert knowledge. The bearing data were used to verify the effect of this method. To tackle the existing challenges in fault diagnosis, a new CNN network was developed. It handles the time-domain raw signal directly, eliminating the requirement for a time-consuming feature extraction step, reducing the reliance on expert knowledge. The findings revealed that, while the most advanced deep neural network model had great accuracy for a regular data set, its performance gradually degraded when there was change in workload. DFCNN, on the other hand,

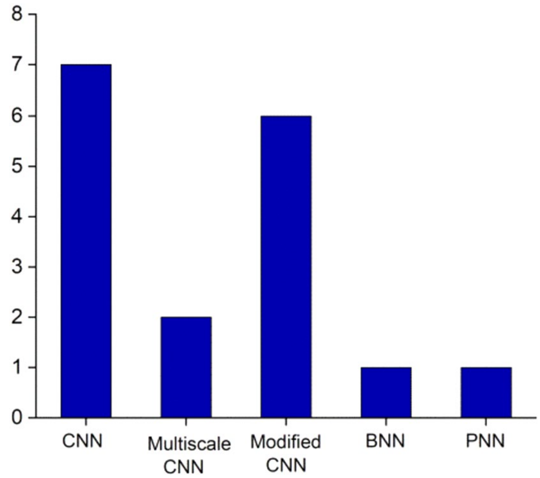

Fig. 5 Represents the total number of times a type of neural network used in the research papers referred

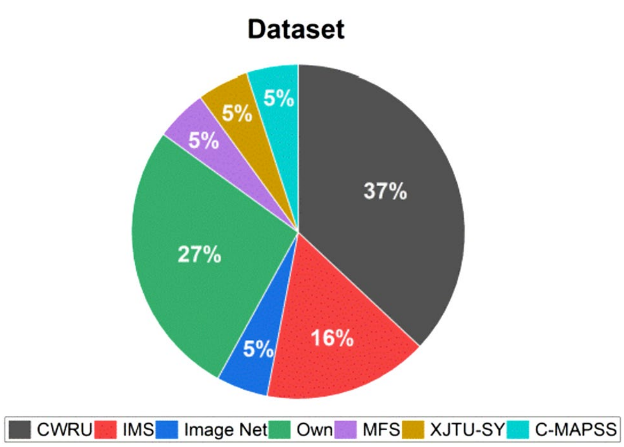

Fig. 6 Represents the total number of times a type of dataset used in the research papers

had a high classification accuracy on normal data and it was very adaptable to workload variations.

In Wentao Mao et al. [59] proposed a combination of Deep feature representation and long short-term memory (LSTM). Deep feature extraction was used in bearing deterioration process and temporal regression using LSTM for predicting life of rolling bearings. The basic idea behind this method was to leverage the good feature ability of the deep learning technique and regression ability of the LSTM for temporal information to reduce RUL prediction error while also improving the numerical stability. The bearing degradation process could be better represented by CNN, which could improve RUL prediction performance. The temporal information of the deterioration process could be used by LSTM. Lower prediction error and numerical stability can be achieved with LSTM.

Wenkai Liu et al. [60] proposed a method to reduce the length of the time sequence. Based on a particular LSTM cell structure with a forget gate, this research proposed a low-delay Lightweight Recurrent Neural Network (LLRNN) model for mechanical problem diagnosis. To achieve performance with network model utilizing LSTM or GRU, with a 10% reduction in computational delay, making it more appropriate for real-time fault detection systems.

Figure 5 represents the neural networks used by the researchers for fault diagnosis. The CNN and modifications to CNN are mostly used to automatically acquire the sensitive fault information from the decomposed signal data. In most of the works, the time domain waveform is considered for feature extraction and the other domains of frequency and time–frequency are used in only few works. Figure 6 represents the various datasets used in the research works. Among different datasets, CWRU is the most widely used dataset for data acquisition which is around 37%, followed by researchers own datasets with around 27% of the research papers considered. The IMS dataset follows with 16% of usage and the remaining datasets were rarely used.

Conclusion

Among all the decomposition methods, variational mode decomposition was the most commonly used method and also found to be very effective compared to other methods. The intrinsic time scale method also finds a reasonable part in many research works. When it comes to filtering methods, the adaptive local iterative filtering was used in most of the cases. A sampling frequency of 2000 Hz was considered in most of the experiments. In some cases, the frequency went much beyond 10 kHz.

In the thermal analysis part, the thermal network model and finite element method were used widely. The maximum temperature attained in most of the experiments was above hundred degrees Celsius. The speed and load followed in the different works was mainly above 2000 rpm and 50 kN respectively.

A thorough statistical investigation of several sensor placement strategies for high quality sensing had been reported in the research works using response surface methodology. The main purpose of the study was to discover the most optimal sensor placement, to ensure fault diagnosis efficacy and measurement quality, which is critical for dependable bearing fault diagnosis.

The CWRU dataset was generally used for data acquisition followed by researchers own data set and IMS dataset. The remaining available datasets were rarely used. Also, various types of neural networks were used in which CNN and modifications to CNN were mostly used to automatically acquire the sensitive fault information from the decomposed signal data. The time domain waveforms are used widely for feature extraction.

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