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Vibration Signal-based Early Fault Prognosis: Status Quo and Applications

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Abstract: To implement Prognostics and Health Management (PHM) for industrial systems, it is paramount to conduct early fault prognosis on the systems to ensure the stability and reliability during their entire lifecycles. Investigations on early fault prognosis have been actively carried out, but there is a lack of systematic analysis and summary of the developed methods. To bridge the gap, in this paper, the relevant methods are comprehensively reviewed from the aspects of signal processing and fault identification. Furthermore, the applications of the methods are systematically described. In the end, to further facilitate researchers and practitioners, statistical and comparative analysis of the reviewed methods are given, and future development directions are outlined.

Keywords: Early fault prognosis; Signal processing; Deep learning; Vibration signal analysis

Nomenclature

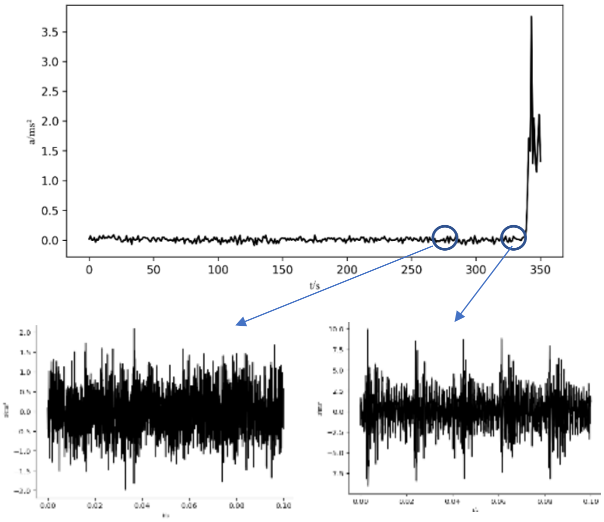
PHM	Prognostics and Health Management
WT	wavelet transform
EMD	empirical mode decomposition
EWT	empirical wavelet transform
VMD	variational mode decomposition
SR	stochastic resonance
IMF	intrinsic mode function
EEMD	ensemble empirical mode decomposition
LMD	local mean decomposition
SVD	singular value decomposition
CNN	convolutional neural network
RNN	Recurrent neural network
DBN	deep belief network
FCM	fuzzy c-mean
SVM	support vector machine
ANN	artificial neural network
KNN	k-nearest neighbour
CMF	combined mode function
CEEMD	complementary ensemble empirical mode decomposition
CEEMDAN	complete ensemble empirical mode decomposition with adaptive noise
HHT	Hilbert-Huang transform
HT	Hilbert transform

FFT	fast Fourier transform
TEO	Teager energy operator
MCKD	maximum correlated kurtosis deconvolution
PSO	particle swarm optimisation
SNR	signal-to-noise ratio
FT	Fourier transform
GA	Genetic Algorithm
QPSO	quantum particle swarm optimisation algorithm
TQWT	Tuneable Q-factor Wavelet Transform
WPT	wavelet packet transform
DWT	discrete wavelet transform
SEI	Shannon entropy index
LS-SVM	least squares support vector machine
CWT	continuous wavelet transform
BPNN	backpropagation neural network
SDAE	stacked denoising autoencoder
SVDD	support vector data description
SAE	Sparse autoencoder
S4VM	safe semi-supervised support vector machine
GRU	gated recurrent unit
DTDA	deep dual temporal domain adaptation
DCAE	deep autoencoder network
RDA	robust deep autoencoder

1. Introduction

Modern industrial systems are characterised as increasingly integrated, autonomous and sophisticated [1-3]. It is vital to conduct an effective prognosis on the health states of the industrial systems, i.e., Prognostics and Health Management (PHM), to maintain stable operations of the systems throughout their lifecycles [4-6]. In the PHM field, numerical research papers have been published and a series of methodologies have been developed [7-9]. The majority of the investigations have been carried out to diagnose faults and identify the faults' severities when the faults have already occurred, i.e., fault diagnosis. Nevertheless, it will be more significant to prognosticate the signs of potential faults (instead of obvious faults already) as early as possible, i.e., early fault prognosis. The early fault prognosis is difficult to be quantitatively described in fault severity identification. It is more beneficial to improve system resilience to prevent the occurrence and development of catastrophic failures of industrial systems incurring significant losses later on [10].

The design of a fault diagnosis method is through scrutinising condition monitoring signals from some key components of industrial systems reflecting the characteristic changes of the systems [11-15]. The signals include vibration signals [16-20], acoustic emission signals [21-25], current signals [26-28], and temperature signals [29-31]. Vibration signals have been popularly used, as abnormal vibrations can reveal the underlying physical phenomena of the monitored components to indicate damage and faults. Nevertheless, early fault prognosis is more difficult to be conducted due to the inconspicuous characteristics of faults [32-34]. Fig. 1(a) shows the kurtosis of the vibration signals on a rolling bearing from a normal condition to a faulty condition. From the 345th minute, the fluctuation of the kurtosis indicates an upward trend, showing the bearing is in a severely damaged condition. Nevertheless, the fault is not obvious during its early development stage. For instance, in Fig. 1(b), the time-domain waveform at the 260th minute (early fault stage) is selected for observation. It can be observed that the kurtosis value at that moment maintains the same level as that of previous periods.



(a) The kurtosis trend for the vibration signals of a rolling bearing.

(b) Signals under the time-domain at t = 260th minute (left) and t = 345th minute (right).

Fig. 1. The kurtosis trend for the vibration signals of a rolling bearing.

During the early stages of a fault (early fault), features are a bit weak and drowned out by the strong background noise. It, therefore, makes early fault prognosis a challenging problem. To address the issue, in recent years, research investigations have been increasingly carried out but a timely summary of the developed methods is lacking. The purpose of this paper is to provide such an update on the relevant research progresses and applications.

The structure of this paper is as follows. Section 1 explains the importance and challenges of early fault prognosis for applications. Section 2 introduces the selection criteria of published papers and the classification schema of the methodologies presented in the papers. In Section 3, key steps of widely used methods in this field are depicted in detail. In Section 4, the applications of the methods are summed up. Section 5 reports the statistical analysis of the published papers and outlines the future research directions. Finally, a summary is given in Section 6.

2. Research Methodology for Review

2.1 Selection criteria of the reviewed literature

Due to the importance of early fault prognostics, in the past years, research works have been effectuated and published in the field. In this survey, there are two steps for identifying and analysing the relevant literatures. Firstly, relevant research works are selected through a keyword search in electronic databases, such as IEEE, ScienceDirect, Elsevier, and Springer online journal collection. Selected keywords include (early fault OR incipient fault OR initial fault OR early failure OR incipient failure) AND (fault prognosis OR fault diagnosis OR fault prediction), etc. Criteria for the selection of literature include: (1) any paper that mentions early faults; (2) journal papers published from 2,000 to the present. In the meantime, the following is used as the exclusion criteria: (1) papers using signals other than vibration signals for analysis; (2) papers not related to the early stages of failure; (3) conference papers, books and review papers. Secondly, the selected papers are fine-tuned through carefully reading and analysing to avoid bias purely on the keyword search, as different percentages of papers could be obtained depending on the interest and preference at the time of keyword selection.

The screening process is shown in Fig. 2. In view of the above criteria and steps, 111 papers were eventually selected for survey in this research.

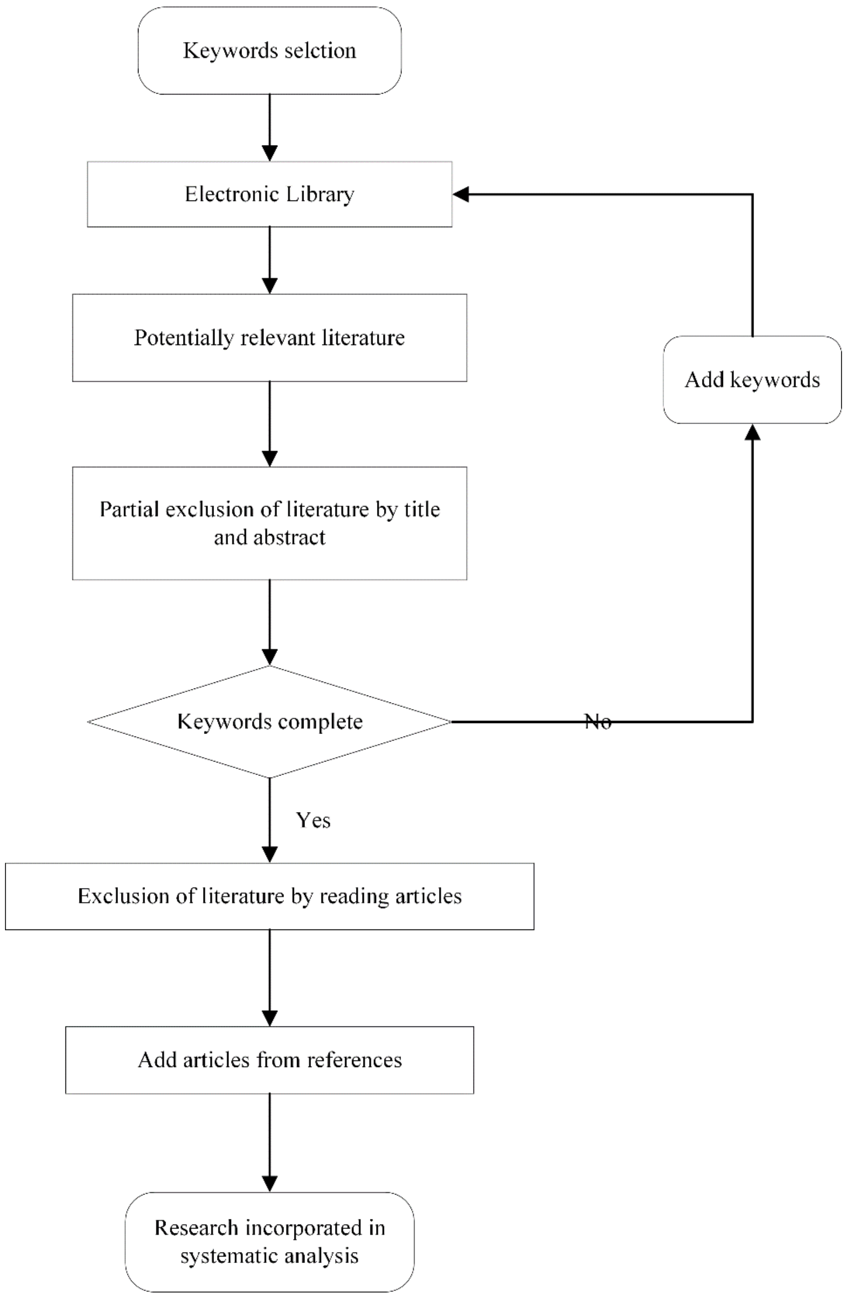


Fig. 2. The search and screening processes of the relevant literature.

2.2 Key stages for early fault prognosis

Early fault prognosis works follow a similar procedure, which includes data acquisition, feature extraction and fault identification. That is, after obtaining vibration signals through sensors mounted on the components of an industrial system (data acquisition), a feature extraction algorithm is then applied to recognise early fault-related features (feature extraction); a method is finally used to classify the fault types (fault identification). Signal acquisition is fundamental to supporting feature extraction and fault identification. Since a comprehensive survey on signal acquisition was already given [35,36], to make this survey more focused, the summary in this paper will be on feature extraction and fault identification. It is assumed that acquainted signals are in good quality and carry sufficient information to support further processing.

In the early fault stage, only tiny damages take place and fault-related features are submerged with background noise. It will be beneficial to design an effective signal processing algorithm to identify weak features from signals containing a large amount of noise [37-39]. Popular signal processing algorithms include wavelet transform (WT) [40], empirical mode decomposition (EMD) [41], empirical wavelet transform (EWT) [42], variational mode decomposition (VMD) [43] and stochastic resonance (SR) [44]. The algorithms can suppress noise and enhance weak features. Fault identification methods are either model-based [45] or data-driven [46]. The former refers to the use of characteristic frequencies for analysis, and the latter refers to the use of artificial intelligent technologies for analysis. Both methods are suitable for periodic fault signals, which are from rotational mechanical equipment. However, only the data-driven methods are effective for abrupt aperiodic signals, such as tool wear in a machining process. The methods will be detailed in Section 3.

3. Key Methods for Early Fault Prognosis

3.1 Feature extraction

In a practical environment, vibration signals contain a large amount of noise, interference signals, and information that does not represent desired fault characteristics. Thus, it necessitates the development of effective signal processing algorithms that can extract features from signals with noise.

The majority of the signal processing algorithms for early fault extraction are through time-frequency analysis. WT is a classic time-frequency analysis method that is based on the short-time Fourier transform with the addition of a changeable time window [47]. In WT, the wavelet transformation is used to remove high-frequency noise in the signals. The selection of a wavelet basis plays a strong influence on the results of wavelet analysis, which makes WT less robust to support applications. Adaptive decomposition methods, represented by EMD [48], were introduced to effectively overcome the shortcomings of WT without requiring a necessary basis function as support. EMD is suitable for non-linear and non-stationary signals. EMD is to decompose the fluctuation or trend of different scales in the signals gradually and generate a series of data sequences with different characteristic scales. Each sequence is called an Intrinsic Mode Function (IMF) [48]. EMD can perform denoising through the rejection of IMFs in different frequency bands.

Nevertheless, there exist some problems in EMD, such as the boundary effect [49], mode mixing [50], overshoot and undershoot [51]. Therefore, EMD was further improved, like Ensemble Empirical

Mode Decomposition (EEMD) [52]. In addition, new adaptive methods, like Local Mean Decomposition (LMD), EWT and VMD, were proposed in order to overcome the limitations of EMD [53-55]. In addition to the aforementioned methods, there are morphological filtering, sparse decomposition, Singular Value Decomposition (SVD) and other methods, which are used for feature extraction and denoising for early fault prognosis.

When signals and noise overlap in the frequency band, the application of the aforementioned methods can lead to information loss when the noise is suppressed. The SR technique is an effective means to resolve this problem [56-59]. It can enhance weak periodic signals in rotating machines [60-62]. However, the classic SR still needs to be further improved and optimised to be used in mechanical fault signal processing [63-65].

In recent years, deep learning algorithms, such as Convolutional Neural Networks (CNN), Recurrent Neural network (RNN), and Deep Belief Network (DBN), have been increasingly applied for early fault prognosis. CNN is currently the most popular neural network in deep learning, which can automatically extract deep features from signals [66]. Compared to CNN, RNN is suitable for the analysis of time-series data owing to its capability of storing the past information, which is commonly used for remaining useful life prediction [67]. For online anomaly detection, models such as deep autoencoder and DBN have been often used for feature extraction [68].

3.2 Fault Identification

3.2.1 Model-based methods

When the contact surface of components in an industrial system is damaged, the metal surfaces in contact will collide with each other during operations. In this situation, low-frequency vibration signals will be generated. These frequencies are related to the structural size of the components and can be calculated, i.e., the characteristic frequency of the fault.

Taking a rolling bearing as an example, the damage on the bearing is the low-frequency vibration caused by the repeated impact of the damage point on the surface of other components. The fault frequency can be calculated from the rotation speed and geometric dimension of the bearing. For a rolling bearing with local fault damages, a large wave peak will appear at the fault characteristic frequency through the signal processing and frequency spectrum analysis. The purpose of the fault identification is to detect the fault characteristic frequency, that is, to find out the obvious fault frequency in the spectrum. The fault type can be judged by the calculated characteristic frequency. The traditional frequency domain analysis approach is difficult to accurately extract the fault characteristic frequency. However, demodulation analysis can judge the fault degree and fault location from the frequency distribution characteristics of the envelope demodulation spectrum [69]. The envelope trace of time-domain signal waveform can be extracted by demodulation analysis. The envelope signal that only contains impact characteristic frequency component attached to the high-frequency natural vibration can be extracted. Then, the detailed spectrum analysis of the envelope signal can be carried out. Popular demodulation technologies include Hilbert demodulation [70] and energy operator demodulation [71].

3.2.2 Data-driven methods

With the rapid growth of the machine learning technology, fault prognosis for industrial systems are gradually transformed into an intelligent way, i.e., data-driven approaches. A data-driven method is to train an intelligent prognosis model and use the trained model to make judgments on real-world data.

Data-driven methods can be further divided into unsupervised and supervised on the basis of underlining intelligent algorithms. Cluster analysis groups data from the same class and separates data from different classes as much as possible according to a certain criterion. This method is an unsupervised learning method to divide samples into classes without training. Clustering analysis can be classified into partition-based algorithms, hierarchical algorithms, density-based algorithms and so on. The main partition-based clustering algorithms include k-means, k-modes, k-medoids, and fuzzy c-mean algorithm (FCM). Taking k-means as an example, it is a typical partition-based algorithm that is iteratively calculated to determine a partitioning scheme of K-clusters by minimising the loss function corresponding to the clustering result. These methods are often applied in the field of early fault prognosis.

The counterpart to the clustering algorithm is the classification algorithm with supervised learning. Commonly used classification algorithms include support vector machine (SVM), artificial neural network (ANN), and k-nearest neighbour algorithm (KNN) [72]. Among them, SVM and ANN are most popularly applied in the field of early fault prognosis [73].

In recent years, deep learning has been applied for early fault prognosis owing to their superior performance than SVM, ANN and other shallow intelligent models [74-76]. Furthermore, in contrast to other traditional data-driven methods, its overwhelming advantage in feature extraction makes it less dependent on signal processing methods in the early fault stage.

4. Early Fault Prognosis Methods and Applications

As aforementioned, an early fault prognosis method is based on the combination of feature extraction and fault identification. In this survey, early fault prognosis approaches are divided into the following four categories (shown in Fig. 3):

(1) Combination of signal processing and model-based methods;

(2) Combination of feature extraction by signal processing and data-driven methods;

(3) Deep learning algorithms;

(4) Methods that do not belong to the above three categories.

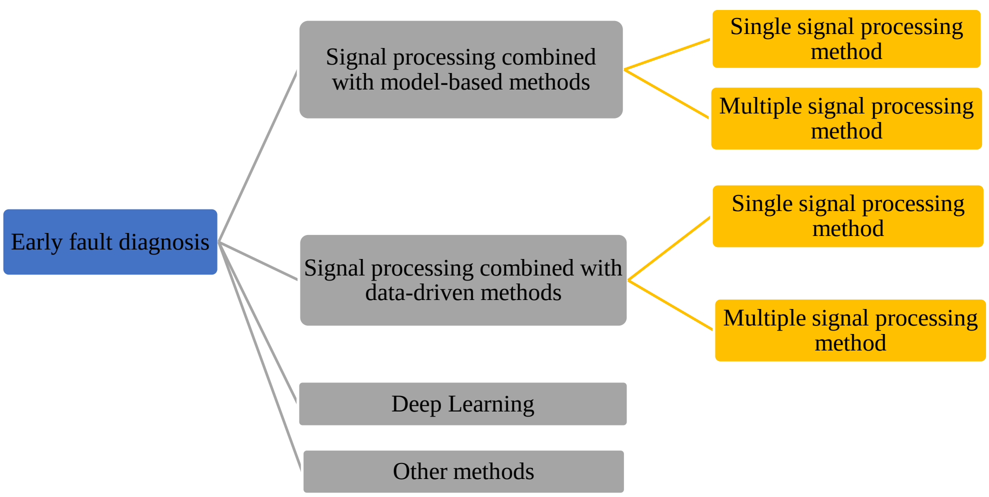


Fig. 3. Early fault prognosis and key constitutive methods with different combinations.

4.1 Combination of signal processing and model-based methods

4.1.1 Single signal processing and model-based methods

Recently, the most dominant approach for early fault prognosis is the application of signal processing methods in combination with model-based methods. The basic process is that a signal processing method is adopted to process the original signal, followed by the spectral analysis on the processed signal. Since the process of spectrum analysis is similar, this section concentrates on noise suppression algorithms. The following is a description of the applications based on the selected literature.

(1) EMD and modified EMD methods

EMD, as a classical time-frequency analysis method, can decompose the original signal adaptively into a series of IMFs. It is a common application to reconstruct the signal after processing the IMFs. Dybała et al. [77] decomposed the vibration signal into IMFs by EMD and aggregated them into three combined mode functions (CMF). Fault identification was carried out with the use of spectrum analysis of empirically determined local amplitudes. Cai et al. [78] estimated 1.5-dimensional spectrum of the selected IMFs obtained by EMD and reconstructed the 1.5-dimensional spectrum of the raw signal for fault diagnosis. Li et al. [79] used an EMD method to identify the characteristic frequency of faults for a gripper cylinder. Abdelkader et al. [80] proposed a method to denoise IMFs obtained by EMD through the optimized threshold operation and to determine the fault location by envelope spectrum analysis.

Since EMD itself has defects such as modal mixing, the improved EEMD, complementary ensemble empirical mode decomposition (CEEMD), complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN), etc. are currently applied to signal processing widely. In order to alleviate the problem of mode mixing in EMD, Lei et al. [81] proposed the EEMD method to process the raw signal and recognise faults through spectrum analysis. To improve the accuracy of Hilbert-Huang Transform (HHT) filtering in rotating machinery for fault prognosis, Lei et al. [82] put forward an improved HHT filtering method based on EEMD and sensitive IMF. Li et al. [83] calculated the cross-correlation coefficient between the original signal and the IMFs obtained via CEEMD. It forms a new signal and then calculated the characteristic frequencies to identify faults by Hilbert transform (HT) and fast Fourier transform (FFT). Chen et al. [84] combined EEMD with Hilbert square demodulation for early fault prognosis for gearboxes. Imaouchen et al. [85] utilised CEEMD to obtain IMFs, and introduced a frequency-weighted energy operator to extract amplitude and frequency modulation from selected IMFs. Karatoprak et al. [86] applied a median filter with variable window size to EMD to obtain an improved Median EMD method and distinguished faults by calculating characteristic frequencies. Yuan et al. [87] proposed a new dual-mode noise reconstructed EMD for weak feature extraction and analyse the IMFs for early fault detection.

(2) VMD and EWT

To overcome the shortcomings of EMD, in addition to its improvement, time-frequency analysis methods such as VMD and EWT have been proposed, which are also applicable to weak feature extraction of the original signal. Jiang et al. [88] used EWT and Teager energy operator (TEO) to further enhance the fault correlation pulse, and envelope spectrum analysis was used to identify faults. To overcome the shortcomings of HHT, Merainani et al. [89] applied EWT with HT for early fault prognosis. Lu et al. [90] utilised a sparse-based EWT to filter the pre-processed the signal and HT to identify faults.

Ma et al. [91] put forward an approach to predict the rolling bearing's early faults based on improved VMD and TEO demodulation. Chegini et al. [92] decomposed vibration signals by an EWT method, then denoised the signals by an improved threshold function, and detected the early fault by using kurtosis parameters and envelope spectrum of the denoised signals. Wang et al. [93] combined a modified EWT using the cuckoo search algorithm with computational order tracking and singular value ratio spectrum to denoise the envelope signal. The denoised signal was eventually analysed for fault identification. Xu et al. [94] utilized VMD optimized by variable dimension chaotic pigeon-inspired optimization algorithm and the TEO for early fault prognosis. Zhao et al. [95] applied VMD and spectrum analysis for early fault prognosis of a wind turbine. Ding et al. [96] combined VMD algorithm using genetic mutation particle swarm optimisation (PSO) to improve the parameters with envelope spectrum analysis for early fault prognosis on rolling bearings. Wang et al. [97] proposed an early fault prognosis method based on parameter adaptive VMD using beetle antennae search and Hilbert demodulation. Zhang et al. [98] combined EWT with a two-layer sliding correlation Kurtosis algorithm to denoise the signal. The envelope spectrum was then used to determine the failure type.

(3) Other time-frequency analysis methods

In addition to some of the common time-frequency analysis methods mentioned above, other methods are used for signal processing. For instance, Feng et al. [99] put forward an amplitude frequency joint demodulation method based on LMD for planetary gearbox's fault prognosis. Based on the fixed cubic Hermite multiwavelets, Yuan et al. [100] used multiwavelets transform with the local spectral entropy minimisation rule and the squared spectrum to detect early fault. Zhao et al. [101] proposed a weighted SVD strategy for signal denoising and verified the validity of the method using envelope spectrum. Dybała [102] proposed a signal decomposition method based on amplitude level, which was used to decompose the signal to get the low amplitude component, and then the local amplitude determined by experience was used for spectrum analysis. Li et al. [103] proposed a multi-fault detection method based on a Bi-component sparse low-rank matrix separation, and employed Hilbert envelope spectrum to identify fault characteristic frequencies. Pang et al. [104] utilised enhanced SVD to denoise the optimal notch filter signal and recognised faults through envelope spectrum analysis. Chen et al. [105] introduced an adaptive chirp mode decomposition method, which used greedy algorithm to capture each signal component and extract the fast fluctuating intermediate frequency of rub impact rotor vibration signal. Based on Dempster-Shafer evidence theory, Xu et al. [106] integrated multiple time-frequency indexes to establish the objective function. After decomposing the reconstructed frequency band, the reconstructed frequency band with the largest objective function value was selected as the optimal resonant frequency band, and demodulated by envelope analysis. Yan et al. [107] used the morphological hat product operation to process the collected weak fault signal, introduced diagonal slice spectrum into morphological analysis to achieve noise suppression and feature enhancement, used the sensitive index of fault feature ratio to determine the optimal scale morphological filtering results, and finally identified faults via failure frequency. Deng et al. [108] proposed a bandwidth Fourier decomposition method, which used bandwidth optimization to improve spectrum decomposition. After pre-processing the original signal with recursive singular spectrum decomposition, Wang et al. [109] selected the most sensitive singular spectrum component by using the envelope spectrum peak index, and analysed the envelope spectrum of deconvolution signal to detect fault. Zheng et al. [110] proposed a bearing fault prognosis method based on low rank and group sparse decomposition of Hankel matrix for noise removal and envelope spectrum was performed for fault identification. Zhou et al. [111] came up with a method based on a combination of attenuated cosine dictionary and feature-sign search to extract fault feature frequencies. Jia et al. [112] designed a modified spectral kurtosis method based on maximum correlated kurtosis deconvolution (MCKD) applied to early fault prognosis.

(4) Stochastic resonance

Nevertheless, the aforementioned methods also exhibit the drawback of possible elimination of useful information. Therefore, SR was developed to avoid such problems. Cao et al. [113] proposed a Fokker-Planck model with smoothly quadratic double well potential combined with power spectrum analysis in order to identify the weak flutter component in the processing signal. Hu et al. [114] applied a SR model to detect the weak frequency component signal representing the beginning of rub impact fault in a rotor system. Wang et al. [115] used the criterion of generalised multi-scale permutation entropy screening to select the signal as the input of the SR system optimised by PSO. Zhang et al. [116] proposed an approach based on the normalised scaling transform SR and Hilbert demodulation for early fault prognosis. Guo et al. [117] utilised multi-stage cascade stochastic resonance using the joint signal-to-noise ratio (SNR) as the evaluation index and spectrum analysis for early fault prognosis. He et al. [118] proposed a new multi-scale noise tuning method, which transforms the multi-scale noise into approximate 1/F to achieve stochastic resonance at a fixed noise level. He et al. [119] realised stochastic resonance on each scale of time-frequency distribution, collected the output spectrum of stochastic resonance in all frequency ranges, and then generated stochastic resonance response. The validity of the method was confirmed by the power spectrum results. Leng et al. [120] developed a new rescaled frequency SR method to meet the requirement of small parameters. Dang et al. [121] selected the signal in view of permutation entropy to input into the Duffing oscillator SR and analysed the spectrum to identify faults. Li et al. [122] applied piecewise nonlinear potential and spectral analysis to perform early fault prognosis. Li et al. [123] combined the SNR, the correlation coefficient between the main components and the original signal, and the zero crossing rate to provide a comprehensive quantitative index for the adaptive stochastic resonance system. FFT+ Fourier transform (FT) discrete spectrum correction was used for the evaluation of the condition of bearings. Lei et al. [124] proposed an underdamped stochastic resonance method with steady-state matching for bearing early fault prognosis and the performance of the method was tested by spectral analysis. Yin et al. [125] adopted an adaptive SR method based on the state transition algorithm and spectral analysis for weak fault prognosis.

(5) Modified stochastic resonance methods

Although the directions of SR improvement are described in the previous section, SR was often improved in multiple directions in practical applications. Wang et al. [126] proposed a new method named Adaptive Multiscale Noise Tuning SR optimized simultaneously by weighted power spectrum Kurtosis and artificial fish swarm algorithm and finally verified the performance of the method with spectral analysis. Ren et al. [127] applied the second-order underdamped continuous potential stochastic resonance method optimised by ant colony algorithm to the early fault prognosis of rolling bearings, and used FT to identify feature frequencies. Zhao et al. [128] developed a new method based on dual scale cascade adaptive stochastic resonance and spectrum analysis. He et al. [129] used an EMD-based multiscale noise tuning method, normalised scaling transform and Genetic Algorithm (GA) to optimise the SR system multilaterally and examined the output signal of the optimised SR system by spectral analysis. Xia et al. [130] designed an improved underdamped periodic SR method using GA to optimise parameters and identified faults by obtaining characteristic frequencies from the spectrum. Xia et al. [131] used an information graph method to process the original vibration signal, and combined the quantum genetic algorithm with the time domain zero-crossing index to optimise the underdamped well-width asymmetric bistable SR system. Han et al. [132] applied adaptive stochastic resonance with a quantum particle swarm optimisation algorithm (QPSO) to cascade a piecewise linear system to extract weak features of the system, and used the output frequency spectrum to implement early fault prognosis. Li et al. [133] proposed multi-parameter constrained potential underdamped stochastic resonance with weighted ant colony algorithm to optimise the parameters, and the spectrum analysis was used to recognise early bearing failures. Lai et al. [134] applied the parameter adjustment SR in the standard underdamped tristable system combined with spectrum analysis to achieve early fault prognosis. Wang et al. [135] developed an adaptive piecewise hybrid stochastic resonance method with three-dimensional inverse positioning and least square method to optimising parameters for early fault prognosis. Lai et al. [136] overcame the small parameter limitation of SR by adjusting the scale and the damping ratio parameter, and used spectral analysis for fault detection.

The applications regarding the combinations of single signal processing methods with model-based methods are specified in Table 1. A further comprehensive performance evaluation from six aspects regarding the reviewed papers (applied to all the tables in this paper):

Capability 1: high sensitivity to early fault detection;
Capability 2: ability to enhance fault features so as to effectively identify weak faults;
Capability 3: ability to accurately identify the type or the location of the fault;
Capability 4: ability to detect early faults in time or online;
Capability 5: algorithm of simplicity or high efficiency;
Capability 6: feasibility for strong noise environment.

Due to the large number of papers in this section, articles that satisfy two or more capabilities are selected for display in Table 1.

Table 1
Single signal processing and the model-based method for early fault prognosis:

Year	Studied Object	Proposed Methodology	Performance Evaluation						Ref
			Capability 1	Capability 2	Capability 3	Capability 4	Capability 5	Capability 6	
2003	Rotor	SR + spectrum analysis		√			√		[114]
2006	Metal Cutting	Re-scaling frequency SR + spectrum analysis		√				√	[120]

Year	Studied Object	Proposed Methodology	Performance Evaluation						Ref
			Capability 1	Capability 2	Capability 3	Capability 4	Capability 5	Capability 6	
2013	Rolling Bearing	EMD + combined mode functions + spectrum analysis	√	√					[77]
2014	Rolling Bearing	CEEMD+ cross-correlation coefficient + Hilbert Transform (HT) + Fast Fourier Transform (FFT)		√			√		[83]
2015	Rolling Bearing	Adaptive multiscale noise tuning SR + spectrum analysis		√		√			[126]
2016	Gear	EMD + 1.5-dimension spectrum		√		√			[78]
2017	Gripper Cylinder	EMD + spectrum analysis			√	√			[79]
2017	Rolling Bearing	CEEMD + frequency-weighted energy operator		√			√		[85]
2017	Gearbox	EWT + HT	√	√		√			[89]
2017	Rolling Bearing	Underdamped SR + spectrum analysis		√				√	[124]
2017	Rolling Bearing	Cascaded piecewise-linear SR + quantum particle swarm optimization (QPSO) + spectrum analysis		√			√		[132]
2018	Rolling Bearing	GA + underdamped periodic SR + spectrum analysis		√				√	[130]
2018	Rolling Bearing	Optimal notch filter + enhanced SVD + envelope spectrum		√				√	[104]
2018	Rolling Bearing + Gearbox	Bi-component sparse low-rank matrix separation + Hilbert envelope spectrum			√			√	[103]
2019	Rolling Bearing	Median EMD + spectrum analysis	√	√					[86]
2019	Rolling Bearing	Attenuated cosine dictionary + feature-sign search + spectrum analysis		√	√			√	[111]

Year	Studied Object	Proposed Methodology	Performance Evaluation						Ref
			Capability 1	**Capability 2**	**Capability 3**	**Capability 4**	**Capability 5**	**Capability 6**	
2019	Rolling Bearing	EWT + cuckoo search algorithm + computational order tracking + singular value ratio spectrum + envelope spectrum		√	√				[93]
2019	Rolling Bearing	Piecewise nonlinear SR + spectrum analysis		√	√			√	[122]
2019	Centrifugal compressors	Multiscale noise tuning + normalized scale transform SR + spectrum analysis		√		√			[129]
2020	Rolling Bearing	Beetle antennae search + VMD + Hilbert demodulation		√				√	[97]
2020	Rolling Bearing	Genetic mutation particle swarm optimisation + VMD + envelope spectrum analysis		√	√				[96]
2020	Rolling Bearing	EWT + two-layer sliding-correlated Kurtosis + envelope spectrum	√	√				√	[98]
2020	Rolling Bearing	Generalized multiscale permutation entropy + PSO + SR + spectrum analysis		√				√	[115]

The number of published papers' distribution by year is displayed in Fig. 4. Since 2017, there has been an explosion of research on early fault prognosis using signal processing methods with model-based methods. Due to the wide range of signal processing methods, there are still a great potential for further development. Also, many different spectral analysis methods have been used in the literature. In the future, more spectral analysis methods may be discovered to diagnose early failures based on the working mechanisms of equipment. Model-based methods have a lot of rooms for further development in handing complex environments.

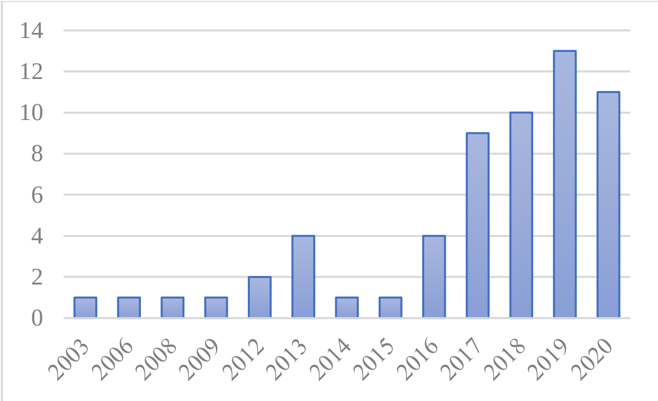


Fig. 4. Publications for the combination of single signal processing and model-based methods.

4.1.2 Multiple signal processing and model-based methods

The methods described in the previous sub-section all used a single signal processing method, but there are also a lot of research works employed multiple methods to be combined with model-based methods. The fact is because, although it is a matter of using one signal processing method to achieve good results, no a single method is perfect. Using multiple methods in combination can provide better results for later fault diagnosis by strengthening the strengths and avoiding the weaknesses. Li et al. [137] proposed a bandwidth based method to select the best envelope interpolation for EMD, and introduced adaptive multiscale morphological analysis to demodulate the constructed principal components. Wang et al. [138] designed adaptive parameter optimised VMD and singular kurtosis difference spectrum to process signals, and Hilbert envelope spectrum was adopted for fault recognition. Lu et al. [139] applied dual-tree wavelet transform and morphological component analysis to signal processing of early fault prognosis, and Hilbert transform was used to obtain fault frequencies. Chen et al. [140] used resonance-based sparse signal decomposition and multiscale wavelet transform for signal processing and Hilbert demodulation for fault identification. Wang et al. [141] combined EEMD and Tuneable Q-factor Wavelet Transform (TQWT) for noise suppression and envelope demodulation was applied for fault recognition. Jiang et al. [142] used multiwavelet packet to improve EEMD and analyse the EEMD results to judge the fault. Jiang et al. [143] combined EMD with VMD method for noise reduction and adopted Hilbert envelope analysis for failure detection. Lei et al. [144] extracted additional fault feature information by HT, wavelet packet transform (WPT) and EMD. Lv et al. [145] utilised nonlocal mean denoising method combined with multivariate EMD to pre-process and analyse multivariate signals to extract fault features, and then used spectrum analysis to obtain characteristic frequencies for fault recognition. Sachan et al. [146] applied a zero frequency filter and discrete wavelet transform (DWT) for noise removal and spectrum analysis to achieve fault recognition.

In signal processing methods, noise suppression methods and feature enhancement methods could be used in combination. This allows both suppression of background noise and enhancement of useful information, which theoretically will make the signal features more obvious. After a modified EMD algorithm was used to denoise the bearing fault signal, Zhang et al. [147] applied MCKD to enhance the periodic impulse signal after denoising the bearing fault signal with a modified EMD algorithm, and finally performed fault identification by spectrum analysis. Wang et al. [148] combined EMD with SR for signal processing and utilized power spectrum for fault identification in the early fault detection of bearings. He et al. [149] combined CEEMDAN with adaptive underdamped SR for noise reduction and feature enhancement, and recognized faults through spectral analysis. Lv et al. [150] performed EEMD on the signal followed by enhancement of the shock components using MCKD to output fault detection results from the envelope spectrum. Chen et al. [151] combined EEMD and adaptive SR with spectral analysis for gearbox early fault prognosis. The applications of the works are shown in Table 2.

Table 2
Multiple signal processing and model-based methods for early fault prognosis:

Year	**Studied Object**	**Proposed Methodology**	**Performance**						**Ref.**
			Capability 1	**Capability 2**	**Capability 3**	**Capability 4**	**Capability 5**	**Capability 6**	
2010	Gear	EMD + wavelet packet transform (WPT) + HT			√				[144]
2013	multi-fault	EEMD + multiwavelet packet + HHT			√				[142]
2014	Rolling Bearing	EEMD + TQWT + envelope demodulation		√					[141]
2015	Rolling Bearing	EMD + MCKD + spectrum analysis				√		√	[147]
2015	Gearbox	EEMD + ASR + spectrum analysis		√	√				[151]
2015	Rotating Machine	EEMD +MCKD + envelope spectrum		√				√	[150]
2016	Rolling Bearing	Nonlocal means + multivariate EMD + spectrum analysis		√					[145]
2017	Rolling Bearing	Bandwidth EMD + adaptive multiscale morphological analysis + demodulation analysis		√					[137]
2018	Rolling Bearing	EMD + VMD + Hilbert envelope analysis		√				√	[143]
2019	Rolling Bearing	CEEMDAN + AUSR + spectrum analysis		√					[149]
2019	Gearbox	Adaptive parameter optimized VMD + singular kurtosis difference spectrum + Hilbert envelope spectrum		√				√	[138]
2019	Rolling Bearing	Dual-tree WT + morphological component analysis + Hilbert transform		√	√				[139]
2019	Rolling	Resonance-based sparse signal		√				√	[140]

Year	Studied Object	Proposed Methodology	Performance						Ref.
			Capability 1	Capability 2	Capability 3	Capability 4	Capability 5	Capability 6	
	Bearing	decomposition + multiscale WT + Hilbert demodulation							
2020	Rolling Bearing	EMD + SR + power spectrum						√	[148]
2020	Rolling Bearing	WT + Zero Frequency Filter + spectrum analysis						√	[146]

The annual number of publications on this category of methods can be seen in Fig. 5. Currently, there are fewer studies using multiple signal processing methods to obtain more obvious features. However, it is feasible to combine several signal processing methods to complement each other to improve the prognostic accuracy. It also suggests that there is significant scope for research.

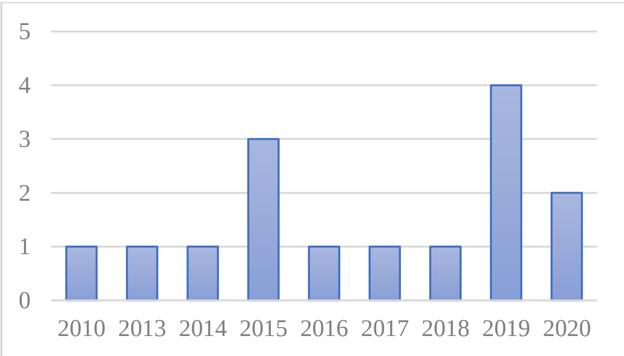


Fig. 5. Publications for the combination of multiple signal processing and model-based methods.

4.2 Combination of signal processing and data-driven methods

4.2.1 Single signal processing and data-driven methods

While the previous section mentioned the combinations of signal processing methods with model-based methods, this section describes the applications of signal processing methods in combination with data-driven methods. Apart from the different fault identification methods used, the difference between the two lies in that the feature parameters, which include statistical features, nonlinear parameters, etc, need to be extracted as input to the data-driven methods. Entropy is an important nonlinear feature of time series that varies with the state of the system and is adopted as feature for early fault prognosis. Yang et al. [152] proposed a fault prognosis method based on EEMD, sample entropy and SVM. Aiming at the problem of weak early fault features of rolling bearings, Zheng et al. [153] proposed a method of fault feature extraction and fault pattern recognition based on VMD, permutation entropy and SVM. Gomez et al. [154] utilised EMD for signal processing to obtain the Shannon entropy index (SEI) and used a decision tree classifier to classify the resulting SEI to detect the early corrosion damage of truss-type bridge. After the EEMD decomposition of the signal, Zhao et al. [155] used the multi-scale fuzzy entropy as the input eigenvector of the SVM model. Deng et al. [156] decomposed the vibration signal into IMF by EMD and calculated the fuzzy information entropy of IMF as the eigenvector. Then, the parameters of the least squares support vector machine (LS-SVM) were optimized by improved PSO algorithm to construct the optimal LS-SVM classifier for fault classification. Liu et al. [157] used the improved EMD algorithm of quartic C2Hermite interpolation to decompose and reconstruct the original signal and then calculated the kurtosis and approximate entropy as the feature values which were used as the input of SVM for early fault prognosis. Xiao et al. [158] applied improved EMD to decompose the signal to get IMFs, and extracted the improved EMD energy entropy as the input of SVM for failure detection.

As can be seen, SVM is chosen in the two examples given above as the fault identification method. SVM is a commonly used data-driven method in early fault prognosis due to its simple algorithm and certain robustness. Inturi et al. [159] used DWT to process the signal and selected features by a decision tree as the input of SVM. Wu et al. [160] proposed a SVM algorithm based on continuous wavelet transform (CWT) and classification tree kernels to identify bearing faults. In addition, there are many other intelligent identification methods for fault identification. For example, Cui et al. [161] denoised the vibration signal by wavelet and used the grey correlation method to locate the fault. Rai et al. [162] used EMD to extract fault features from bearing signals. Then, the extracted features are clustered based on K-medoids. Zhang et al. [163] utilised EEMD for feature extraction and backpropagation neural network (BPNN) for fault identification. Table 3 depicts all the approaches mentioned above.

Table 3
The combination of single processing and data-driven methods:

Year	**Studied Object**	**Proposed Methodology**	**Performance**						**Ref.**
			Capability 1	**Capability 2**	**Capability 3**	**Capability 4**	**Capability 5**	**Capability 6**	
2016	Rolling Bearing	WT + grey correlation method		√	√			√	[161]
2017	transmission system	Improved EMD + PSO-SVM			√				[158]
2017	Rolling Bearing	EMD + multiscale fuzzy entropy + SVM		√	√				[155]
2017	Rolling Bearing	EMD + k-medoids clustering		√					[162]
2017	Rotor	EEMD + BPNN		√					[163]
2017	Rolling Bearing	CWT + classification tree kernels SVM			√				[160]
2018	Truss-type Bridge	EMD + SEI + decision tree		√	√		√		[154]
2018	Rolling Bearing	EEMD + sample entropy + SVM			√				[152]
2019	High-Speed Rails	Improved EMD + approximate entropy + SVM			√				[157]
2019	Rolling Bearing	EMD+ fuzzy information entropy +			√				[156]

Year	Studied Object	Proposed Methodology	Performance						Ref.
			Capability 1	Capability 2	Capability 3	Capability 4	Capability 5	Capability 6	
		PSO-LSSVM							
2019	Rolling Bearing	VMD + permutation entropy + SVM			√	√			[153]
2020	Gearbox	DWT + SVM			√				[159]

The annual number of publications in the selected literature can be shown in Fig. 6. There are many data-driven methods that can be used for fault identification, although at present there are still relatively few applications in the field of early faults and only the more classical methods are often used. Future developments can be expected.

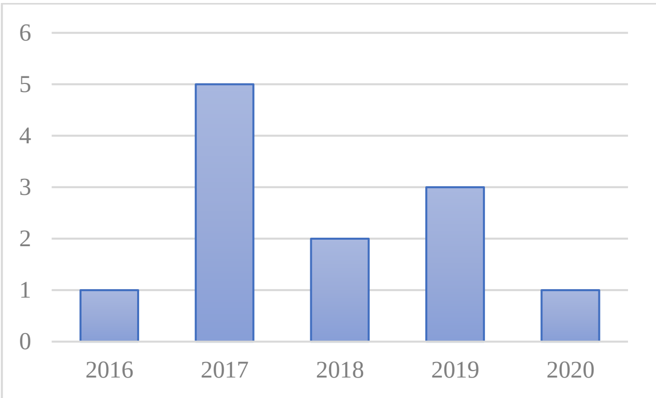


Fig. 6. Publications for the combination of single signal processing and data-driven methods.

4.2.2 Multiple signal processing methods and data-driven methods

This section focuses on the application of using a combination of multiple signal processing methods and data-driven methods. Since the difference between multiple noise suppression methods and single noise suppression methods has been mentioned previously, it will not be repeated here. Bin et al. [164] decomposed the signal into a series of narrow bandwidths by using WPT denoising method, then obtained the IMF of corresponding band characteristics by using EMD, and used BPNN for fault identification. Wang et al. [165] extracted early fault features using WPT following the enhancement of fault information by means of SR for input into SVM for diagnosis. Tabrizi et al. [166] used WPT to filter the collected noise signal, and then used EEMD technology to extract the information feature vector as the input of SVM. Gai et al. [167] used EMD and SVD in signal processing, and used fuzzy neural network for classification. Dovedi et al. [168] combined EMD and TQWT to process the signal, and used SVM to recognize the state.

Table 4 summarises the applications in the selected papers mentioned above. It can be found that there are fewer applications in this section, presumably because the combinations of data-driven and noise-suppression methods are more focused on feature extraction in signal processing than the combinations of model-based and noise-suppression methods. Moreover, multiple noise suppression methods, whether combined with model-based methods or data-driven methods, have a small number of applications and have great potential for investigation.

Table 4

The combination of multiple noise suppression and data-driven methods:

Year	Studied Object	Proposed Methodology	Performance						Ref.
			Capability 1	Capability 2	Capability 3	Capability 4	Capability 5	Capability 6	
2012	Rotor	WPT + EMD + BPNN		√				√	[164]
2015	aeroengine rotor system	SR + WPT + SVM		√		√			[165]
2015	Rolling Bearing	WPT + EEMD + SVM			√			√	[166]
2019	Rolling Bearing	EMD+SVD+ fuzzy neural network		√		√			[167]
2020	Rolling Bearing	EMD + TQWT + SVM			√				[168]

4.3 Deep learning algorithms

In recent years, the application of the deep learning method in early fault prognosis has been developed rapidly due to its adaptive property for feature extraction and end-to-end characteristics. Mao et al. [169] combined SVD, EMD and kurtosis in order to determine the starting point of early faults, and hired stacked denoising autoencoder (SDAE) to extract healthy and early fault features, which were input to the training support vector data description (SVDD) for anomaly detection. Hu et al. [170] utilised the optimal EWT to decompose the original signal and employed CNN to extract sensitive features to make FCM recognise faults. Luo et al. [171] trained the model by combining Sparse autoencoder (SAE) with BPNN, and employed dynamic characteristic similarity to construct an indicator for fault monitoring. Mao et al. [172] adopted SDAE to extract deep features which are fed into safe semi-supervised SVM (S4VM) for anomaly detection. Wang et al. [173] directly adopted the DBN algorithm that adopted QPSO to determine the hidden layer structure and learning rate to extract features as input of SVM.

In addition to its own powerful feature extraction capabilities, deep learning is also a data-driven approach that allows for direct classification. Liang et al. [174] presented a novel approach based on WT and CNN to complete the fault detection of rotating machinery. Yang et al. [175] pre-processed the raw signal through VMD optimised by GA as the input of CNN for early fault prognosis. Shao et al. [176] used the complex WPT energy entropy of the signal as an indicator to train the enhanced deep gated recurrent unit (GRU) for early fault prognosis.

Furthermore, there are cases that deep learning is applied for feature extraction and fault identification. Roberto et al. [177] input the FFT data into the predictive maintenance model with CNN to diagnose faults in rotating machinery. Yang et al. [178] designed a sliding scale resampling strategy to construct a balanced sample set, and constructed an SAE with multi-particle noise addition model to identify the type and severity of failures. Zhang et al. [179] input multi-scale signals into multiscale CNN model through multiscale data processing for noise reduction and feature extraction and integrated GRU network with attention mechanism into the fully-connected layer for prediction. Li et al. [180] devised a novel approach based on dilated CNN combined with spatial dropout to solve the problem that CNN will cause feature loss, which is conducive to early fault prognosis.

Transfer learning is an emerging method in the field of fault diagnosis, which can solve the problem of lack of data. Many scholars combine deep learning and transfer learning to construct a deep transfer learning model for early fault prognosis. Mao et al. [181] performed state evaluation of the source signal using HHT and SVDD, and then extracted the common features of the source and target signals through the deep dual temporal domain adaptation (DTDA) model, which was trained for online monitoring. Mao et al. [182] input a set of three-channel data containing time, frequency and time-frequency information into a pre-trained VGG-16 deep CNN to construct a transfer model, which extracts the features of the auxiliary bearing of the health state and inputs the features into SVDD for training fault classification. Shi et al. [183] introduced deep autoencoder network (DCAE) to extract the features of the two data to obtain the common features, which were then used to train temporal CNN for fault monitoring. Mao et al. [184] used a deep autoencoder model with domain adaption to extract common features of bearings and performed state evaluation through robust deep autoencoder (RDA) to construct a detection model by training SVM.

All papers adopting deep learning algorithms are represented in Table 5.

Table 5

Applications of deep learning algorithms in early fault prognosis:

Year	Studied Object	Proposed Methodology	Performance						Ref.
			Capability 1	Capability 2	Capability 3	Capability 4	Capability 5	Capability 6	
2019	Rolling Bearing	SVD + EMD + SDAE + SVDD	√			√			[169]
2019	Machine Tools	SAE + BPNN		√					[171]
2019	Transformer	QPSO + DBN + SVM			√				[173]
2020	Bearing	VGG-16 deep CNN + SVDD				√			[182]
2020	Bearing	Complex WPT + GRU	√		√				[176]
2020	Bearing	Deep autoencoder model with domain adaption + RDA + SVM			√	√			[184]
2020	Bearing	SDAE + S4VM		√		√	√		[172]
2020	Bearing	SAE with multi-particle noise addition		√					[178]
2020	hydraulic pipe clamps in aero-engines	GA-VMD + CNN		√	√				[175]
2020	Rolling Bearing + Gearbox	WT + CNN			√			√	[174]
2021	Rotating machine	FFT + predictive maintenance model with CNN			√				[177]
2021	Bearing	HHT + SVDD + DTDA	√	√		√			[181]

Year	Studied Object	Proposed Methodology	Performance						Ref.
			Capability 1	Capability 2	Capability 3	Capability 4	Capability 5	Capability 6	
2021	Rolling Bearing	DCAE + temporal CNN			√			√	[183]
2021	Rolling Bearing	Optimal EWT + CNN + FCM	√						[170]
2021	Rolling Bearing	Multiscale CNN + GRU Network		√	√				[179]
2021	Gear	CNN + Spatial Dropout			√				[180]

As shown in Fig. 7 below, deep learning algorithms have shown a clear trend of increase. In the application in the early fault area, there is a higher volume of literature using this method. Up to the first half of 2021 the number is nearly at the same level as in 2020. This shows that deep learning algorithms exhibit a great potential for early fault prognosis and represent a popular research direction at present.

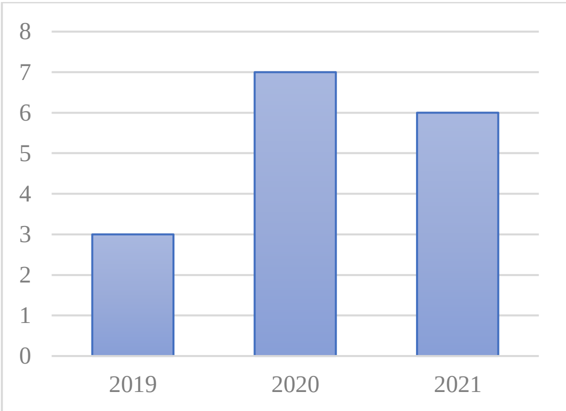


Fig. 7. Publication Distribution with the application of deep learning algorithm in early fault prognosis

4.4 Other methods

There are also some applications of early fault prognosis methods that do not fall into the three categories above, so they are presented separately in this section. In addition to the model-based and data-driven methods, there is another application that simply discriminates early faults from changes in statistical indicators which will exceed a certain threshold value if the system fails. When judging when an early fault occurs, an index can be set as an early warning criterion to replace or be implemented with fault identification methods mentioned above [172]. Usually, the fault type or location at the moment can be recognized after determining the fault at a certain moment [169]. Parey et al. [185] proposed a method for solving EMD boundary distortion with a variable cosine window and followed the variation in indicators such as kurtosis to judge bearing failure. Aiming at the problem that the coupling of multiple faults will affect the diagnosis accuracy, Fan et al. [186] utilised discrete wavelet transform to extract statistical parameters which were used to diagnose and locate gear damage. Chegini et al. [187] employed the change in envelope harmonic noise ratio to identify a moment of bearing failure after the fast ensemble empirical mode decomposition of the raw signal selected the most sensitive IMF. The references are shown in Table 6 below.

Table 6

Applications of other methods in early fault prognosis:

Year	**Studied Object**	**Proposed Methodology**	**Performance**						**Ref.**
			Capability 1	**Capability 2**	**Capability 3**	**Capability 4**	**Capability 5**	**Capability 6**	
2012	Gear	EMD + Cosine Window-based Method	√			√			[185]
2014	Gear	DWT	√	√				√	[186]
2020	Rolling Bearing	fast EEMD		√		√			[187]

5. Analysis of Reviewed Papers

5.1 Statistical Results

Fig. 8 shows the proportion of application objects of early fault prognosis methods in selected journal papers. It can be seen that so far, rolling bearings are still the most concerned and application area for the methods.

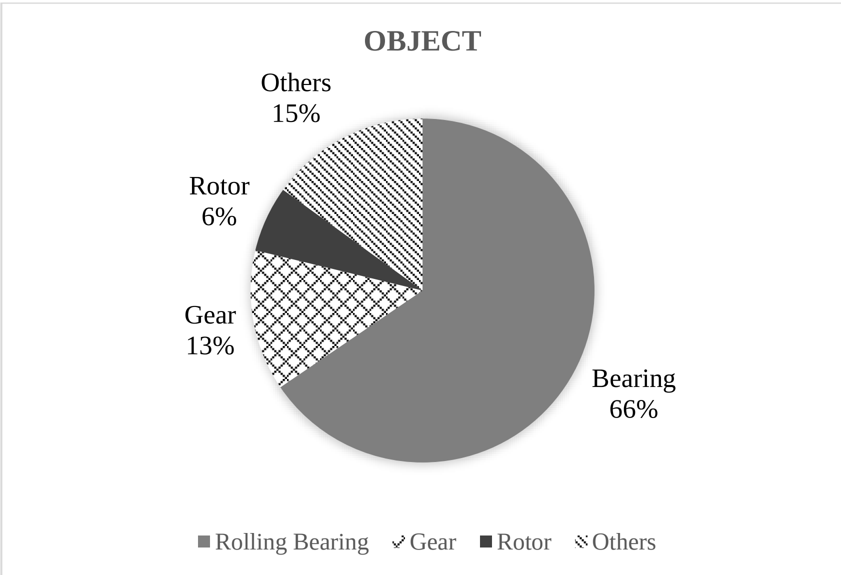


Fig. 8. Proportion of application objects

Statistical analysis was also made on the methods reviewed in this paper. We have summarized that single methods used in some papers have suffered from the problem of difficulty in extracting early fault-related features, and therefore combined methods have been used to achieve better results for this problem. Apart from the deep learning-based methods for early fault prognosis, other methods in the papers have been divided into two parts, i.e., feature extraction and fault identification.

As shown in Fig. 9, most of the papers adopted signal processing methods from the perspective of feature extraction, i.e., 71 out of them selected the time-frequency analysis. The remaining papers selected deep learning to extract deep features, all of which are from recent years. It should be mentioned that 5 papers of them utilised deep learning with signal processing methods. Specifically, EMD accounts for the largest proportion of the feature extraction methods, with 37 papers. This is closely followed by the SR method, which occupies 28 papers. 17 papers employed WT, often in conjunction with other methods. EWT and VMD were used in similar proportions, with SVD and MCKD accounting for a smaller proportion. Although signal processing methods have many applications, deep learning also has an emerging growth. It is mainly because although traditional methods can detect early fault effectively, there is still a strong demand to develop new methods to cope with increasingly complicated systems and working conditions, and deep learning is just the one as such a novel and effective method.

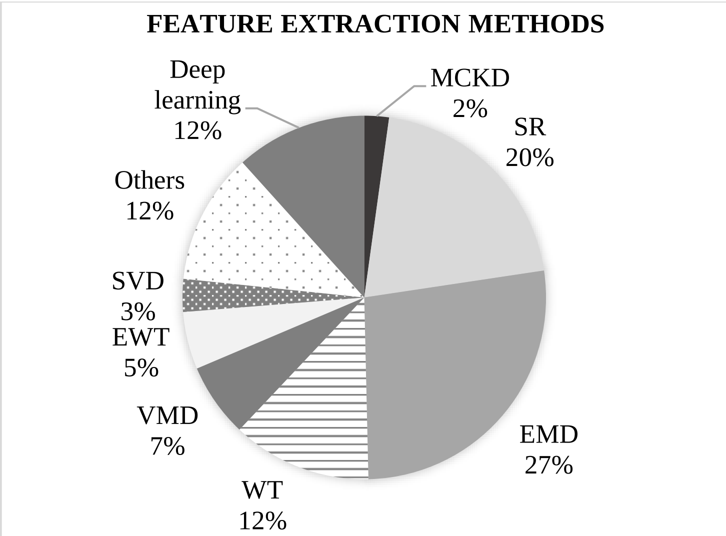


Fig. 9. Proportion of feature extraction methods adopted in selected papers

For the fault identification methods, as shown in Fig. 10 below, the vast majority opt for a model-based approach, with 75 papers, although it is only applicable to rotating machinery. Of the remaining papers, 3 chose to use statistical parameters to determine the state of the bearing. SVM and modified SVM account for nearly half of the papers choosing data-driven methods, i.e., 17 papers. It is closely followed by the deep learning algorithm, i.e., 9 papers. The next more popularly used method is ANN, including 4 papers. Of the remaining papers, 2 chose clustering algorithms and 2 used other methods. In the data-driven method, ANN has the advantages of nonlinearity, self-learning, adaptability and association ability, but it also demonstrates a slow convergence speed and is difficult to determine the number of nodes. In contrast, SVM has a better generalisation ability and a faster training convergence speed, which makes it widely used in mechanical fault prognosis. Nowadays, data-driven early fault prognosis methods have increasingly become the research interests of many scholars, in which deep learning is a popular one. Transfer learning has become a further research direction for early fault prognosis. It is worth noting that there are 4 papers construct deep transfer learning model.

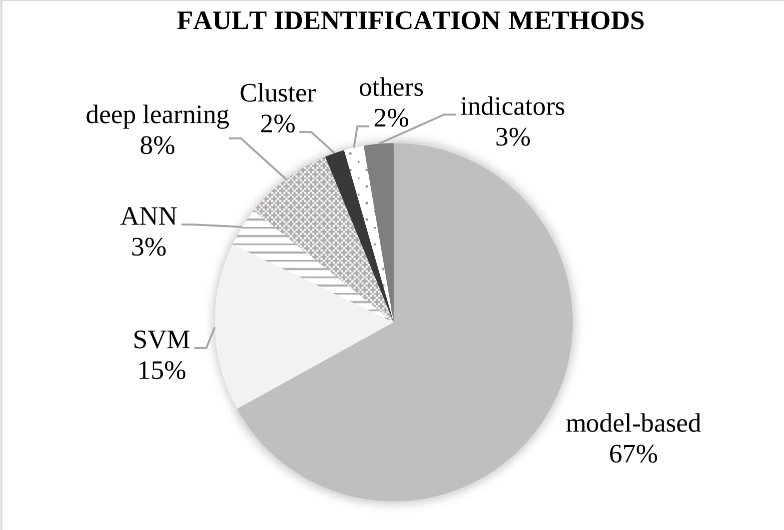


Fig. 10. Proportion of fault identification methods adopted in selected papers

From the above statistics, it appears that model-based methods are the most frequently studied due to their maturity and applicability to real industrial situations. Nevertheless, given the wide range of faults available and the fact that how to detect early faults in time is not thoroughly explored, there is still an improvement scope for data-driven methods. In data-driven methods, most of the shallow classification models have centred on SVMs. More research on early faults has been conducted on feature extraction, where various signal processing methods were employed to capture weak features. Compared to these shallow models, deep learning has a considerable advantage in the study of early faults owing to its ability to extract deep fault features, and there have been substantial achievements in recent years. As the portfolio of methods for early fault prognosis is very diverse, there is still plenty of scope for in-depth research. Therefore, the advantages and disadvantages of some of the methods currently commonly used in the field of early failure are summarised in Table 9 for reference.

Table 9

Pros and Cons of the reviewed methods

Methods		**Advantages**	**Disadvantages**
Signal Processing	WT	Simple and fast	Difficult to select mother wavelet
	EMD	Adaptability	Mode mixing and endpoint effect
	VMD	High resolution; has better anti-mode mixing and anti-noise capabilities	Need to determine the penalty factor and the number of sub modes before operation
	EWT	High operation efficiency; effectively suppress mode mixing and endpoint effect	Difficult to determine the parameters; not suitable for complex faults

	SR	Not remove useful information while suppressing noise	Difficult to meet the requirements of SR in engineering practice
Fault Identification	spectrum analysis	Accurate extraction of fault characteristic frequency	Application scope is limited
	ANN	Nonlinearity, self-learning, adaptability and association ability	Slow convergence speed, easy to get stuck at local optimum and difficult to determine the number of nodes
	SVM	Good generalization ability and overfitting problem is not as much as other methods.	Sensitive to missing data; long training time for large datasets.
	Deep Learning	Powerful feature extraction capabilities	Not adapt to changes in working conditions

Furthermore, some new methods such as graph neural networks have been attempted to be applied in the field of fault diagnosis, but no specific research has been conducted on early faults, which is also a direction worth developing [188]. Li et al. [189] proposed a rolling bearing fault diagnosis model based on horizontal visible graph and graph neural network. Yu et al. [190] presented a novel fast deep graph convolutional network for detecting wind turbine gearbox faults.

As a final addition, the methods mentioned above are not only suitable for vibration signals, but also suitable for other signals [191-194]. For instance, Chen et al. [193] calculated the Kullback-Leibler divergence residuals as the input of a CNN to extract fault features after applying the canonical correlation analysis to the current signal.

5.2 Discussions on further development

In this paper, the application of vibration signal analysis for early fault prognosis is reviewed, while there might be some inevitable omissions. To sum up, from the statistical analysis of the selected literatures, it can be concluded that in practical environment, due to the difficulty of obtaining high-quality fault data, model-based fault prognosis methods are less effective. Instead, data-driven methods are useful because of the high feasibility to handle complex situations like compound faults occurrence. To better promote the development of early fault prognosis, future work might be carried on from the following aspects:

(1) As in the early fault stage, data samples might have the problems of asymmetric distributing and insufficiency. It can be further explored in the direction of unsupervised learning, semi-supervised learning and data generation algorithms in the future. Generative Adversarial Networks, which can resolve the challenging issue of limited data available, is attracting more researchers' attentions.

(2) Since the features of the early fault signal are quite weak, feature extraction for early faults

will continue being a significant research gap to overcome. Deep learning methods will be further explored to accelerate early fault feature extraction owing to their end-to-end characteristics.

(3) Furthermore, for catering with the different operation situations and complex industry environments, deep transfer learning may hold a great promise to be a better solution on early fault prognosis in the coming future.

6. Conclusion

Early fault prognosis is crucial to support PHM for industrial systems. It can improve the reliability of the systems, and reduce the risk of operation crash and catastrophic failures significantly. In recent years, increasing research has been conducted in this field but a timely update is lacking. To bridge the gap, in this paper, the early fault prognosis methods based on vibration signal are systematically reviewed from the aspects of feature extraction and fault identification. Furthermore, the applications of the methods are analysed in detail. Finally, through the statistical analysis of the literature, some important development prospects of this field are pinpointed, providing references and guidelines for researchers and practitioners to further develop and apply the relevant research. It can be found that the model-based approach is one of the widely used approaches in industry. Nowadays, with the rapid development of the machine learning algorithms, the data-based approach is becoming the main direction in the future. The same trend goes for feature extraction approaches. Thus, the powerful capabilities of machine learning algorithms, particularly deep learning algorithms, clearly hold great potentials for the future.

Acknowledgments

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