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REVIEW PAPER

Compound Fault Diagnosis for Rotating Machinery: State-of-the-Art, Challenges, and Opportunities

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Abstract: Compound fault, as a primary failure leading to unexpected downtime of rotating machinery, dramatically increases the difficulty in fault diagnosis. To deal with the difficulty encountered in implementing compound fault diagnosis (CFD), researchers and engineers from industry and academia have made numerous significant breakthroughs in recent years. Admittedly, many systematic surveys focused on fault diagnosis have been conducted by reputable researchers. Nevertheless, previous review articles paid more attention to fault diagnosis with several single or independent faults, resulting in that there is still lacking a comprehensive survey on CFD. Therefore, to fulfill the above requirements, it is necessary to provide an in-depth overview of fault diagnosis methods or algorithms for compound faults of rotating machinery and uncover potential challenges or opportunities that would guide and inspire readers to devote their efforts to promoting fault diagnosis technology more effective and practical. Specifically, the backgrounds, including the related definitions and a new taxonomy of CFD methods, are detailed according to the way of implementing compound fault recognition. Then, the state-of-the-art applications of CFD are overviewed based on relevant publications in the past decades. Finally, the challenges and opportunities associated with implementing CFD are concluded and followed by a conclusion for ending this survey. We believe that this review article can provide a systematic guideline of CFD from different aspects for potential readers and seasoned researchers.

Keywords: fault diagnosis; compound fault; signal processing; artificial intelligence; rotating machinery

I. INTRODUCTION

Modern mechanical machines are complex systems that consist of hundreds or even thousands of components to collaboratively work together for implementing target tasks, and thus a complicated relationship is formatted between these components, which also exerts influence reciprocally. Meanwhile, the critical components are prone to damage or failure because of the harsh working environment, the inappropriate operation, and the fact that machines are running in long-term serves [1,2]. In doing so, the compound fault becomes a majority failure that occurs with high uncertainty and low predictability in practical engineering. Compound fault, also known as composite fault or multiple faults, is the primary cause of unexpected downtime of machines, which would, in turn, result in economic losses and even miserable catastrophes.

Fault diagnosis technology, as a curial part of Prognostics and Health Management (PHM), has become a prevalent tool to ensure the efficiency, stability, and security of mechanical machines in many industrial applications, which not only protects people's property and lives to suffer from catastrophes but also brings strategic significance on the transformation and upgrading of modern manufacture industry. As one of the most common types encountered, rotating machinery is a particularly well-developed field of fault diagnosis that applies. However, the compound fault of rotating machinery dramatically increases the difficulty in fault diagnosis. The difficulty in implementing compound fault diagnosis (CFD) mainly comes from the following three aspects: (1) Compound fault typically occurs and evolves within several key components among which spatial–temporal correlation and interaction exist. (2) The relationship between the compound fault and its corresponding single faults is strongly related, not just linear accumulated. (3) The mechanisms of how the compound fault occurs and evolves are hard to be revealed from the perspective of causality or concluded as general laws.

Although there are many difficulties mentioned above, researchers and engineers from industry and academia have made many significant breakthroughs in CFD in recent years. Therefore, it is necessary to conduct a comprehensive survey for CFD based on the relevant publications. Admittedly, many systematic surveys focused on fault diagnosis have been conducted by reputable researchers, which provide many valuable benefits, including comprehensive critical reviews of the current state-of-the-art, in-depth insight into challenges, limitations, and research directions in the field of fault diagnosis, etc. For instance, Li *et al.* systematically overviewed the intelligent fault diagnosis (IFD) methods for industrial equipment based on deep transfer learning (DTL) technology, in which the industrial scenarios of IFD have been summarized into four categories and their corresponding applications are reviewed in detail [3]. Zhao *et al.* performed a comprehensive survey on unsupervised DTL-based IFD, in

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which an open-source code framework is established, and comparative discussions are presented as baseline results for convenience comparison [4]. Zhang *et al.* summarized the publications which focused on the problem of IFD with small and imbalanced data and pointed out the challenges and directions that should be placed more effort [5]. Similar review articles, which overview the relative literature of fault diagnosis from different perspectives including algorithms [6,7], components [8], PHM tasks [9], etc., can be found and cannot be enumerated here in-depth. Nevertheless, all the review articles mentioned above did not consider the following two aspects: (1) Previous review articles paid more attention to fault diagnosis with several signal or independent faults. It is still lacking a comprehensive survey on CFD, which has more practical significance in industrial scenarios since the compound fault is the primary failure that causes unexpected downtime of machines. (2) It can be found from these historical review articles that the practical challenges and emerging opportunities in fault diagnosis, especially in CFD, are not clear yet. The major concern is that, in industrial applications, a systematic guideline or an appropriate direction matters for developing effective solutions for specific diagnosis problems.

To fulfill the above requirements, hence, the main goal of this survey is to provide an in-depth overview of fault diagnosis methods or algorithms for the compound fault of rotating machinery and uncover potential challenges or opportunities that would guide and inspire the readers to devote their efforts to promoting fault diagnosis technology more effectively and more practically. Specifically, the main contribution of this article is that the state-of-the-art in CFD has been systematically reviewed for the researcher's convenience, and the core challenges, potential opportunities, and future directions that might advance the field of fault diagnosis are analyzed and presented in detail.

In the remainder of this survey, the backgrounds of CFD are introduced in Section II, in which the related definitions and a new taxonomy of CFD methods are detailed according to the way of implementing compound fault recognition. Section III summarizes the state-of-the-art applications of CFD based on the related publications in the past decade. The core challenges and open issues associated with implementing CFD are concluded and discussed in Section IV. Section V offers a conclusion for this survey that has come to an end.

II. BACKGROUND OF CFD

This Section briefly introduces the basic definitions related to CFD and categorizes the CFD methods into three groups, which offers a solid background for newcomers or seasoned researchers and facilitates the discussions on the state-of-the-art applications of CFD in the following sections.

A. DEFINITIONS RELATED TO CFD

As a matter of fact, there is no general definition to describe what is compound fault since it has different manifestation patterns in the different individuals of the same machines, let alone in the different machines. Taking the rotating machine as an example, the primary manifestation patterns of the compound fault include but are not limited to the following three types. (1) Multiple faults in an identical component occur simultaneously. For example, the inner race fault and the outer race fault occur simultaneously, as well as multiple defects occur in the outer race or the inner race. (2) Multiple components of an identical subsystem are damaged sequentially or simultaneously. For example, the bearing fault and the gear fault occur in the transmission gearbox simultaneously. (3) Multiple subsystems of the machine are damaged sequentially or simultaneously. For example, the engine fault and the transmission fault occur in the complex system simultaneously. Fig. 1 shows examples of the above compound fault for helping readers understand it better. Apart from the manifestation patterns, the terminology of compound fault is also known as "multiple faults", "composite fault", "mixed fault", and "combination fault". Such a phenomenon may indirectly illustrate the high complexity of the compound fault. Considering the frequency of the terminology used in publications, in this survey, the "compound fault" is used to represent all the above terminology. Additionally, based on the above explanations, we offer a definition of Compound Fault as "a new failure that is formed by the combination of two or more single faults that occurred in a machine at the same time" for convenience.

No matter how different the manifestation patterns and terminology of compound fault are, some common characteristics can be summarized from the published literature as follows: (1) The compound fault can be regarded as multiple single faults nonlinearly coupled together to form a different but related pattern. Thus, the relationship between the

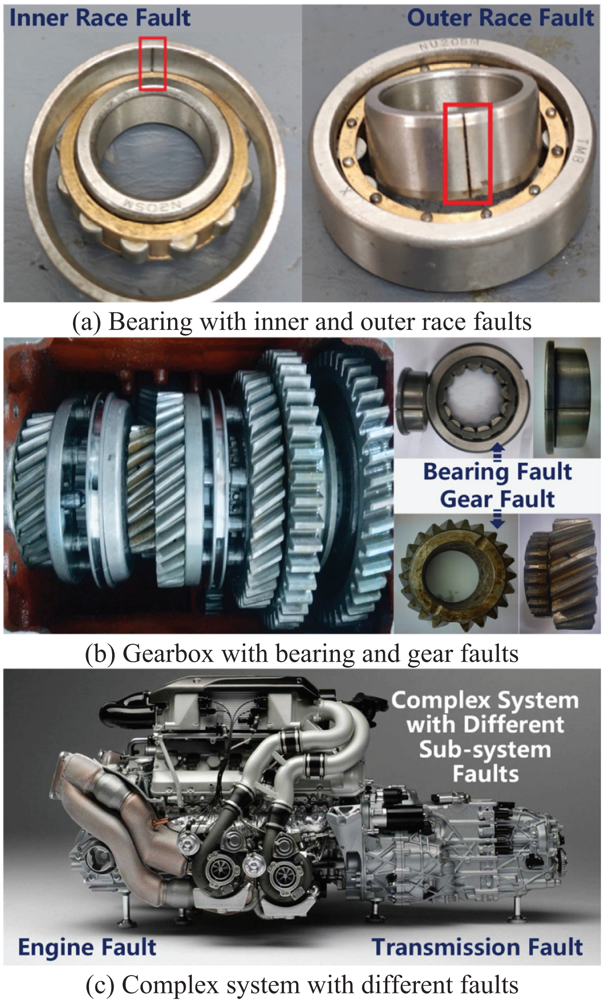

Fig. 1. Examples of compound fault.

compound fault and its corresponding single faults is related but absolute not simply linear accumulated. (2) The different patterns coupled in the compound fault exert influence reciprocally and have spatial–temporal correlation and interaction, resulting in more complicated characteristics than single faults. Furthermore, fault types, sizes, and positions are sensitive factors and deviations that can directly affect the coupled result of the compound fault. (3) It is difficult to establish a precise mathematical or dynamical model based on the physical mechanisms of the compound fault in complex machines because the mechanisms of how the compound fault occurs and evolves are hard to be theoretically explained from the perspective of causality or concluded as general physical laws. Noticing these common characteristics can inspire and allow researchers to exploit effective solutions for implementing the diagnosis of the compound fault.

CFD is a process that determines or infers which faults (typically more than one fault) have occurred in machinery based on analyzing the monitoring data, identifying the types of faults, and distinguishing each fault's location or even judging the size of faults. Compared to regular fault diagnosis, which mainly concerns situations when only a single fault occurs, CFD can be regarded as a more complex diagnosis task, which deals with the more practical situations when multiple faults occurred simultaneously and are coupled with each other. A general way to make a fault diagnosis for a compound fault should consider the following three main questions: (1) whether a compound fault occurs, (2) what faults are coupled in the compound fault, and (3) how to separate these faults.

"Whether a compound fault occurs" asks in which situations CFD should be implemented. In some situations, CFD would be unnecessary when only a single fault happens. Brute-force CFD may even increase the risk of misdiagnosis. Most of the current publications on CFD focus on the latter two issues by implicitly assuming that the compound fault has already occurred.

"What faults are coupled in the compound fault" refers to exploring the most important problem about CFD, that is, what exact faults are coupled together to form the compound fault. However, in practice, there is no prior information that can be known in advance such that it is difficult to directly solve such a problem. Just as mentioned earlier, the compound fault is related but not a linear superposition with its corresponding single faults. Thus, it needs to develop an effective solution that can separate the discriminative characteristics of single faults from the monitoring data of the compound fault.

"How to separate these faults" specifies the form that a CFD method takes. The motivation behind these methods is to imitate the ability of human beings who can easily recognize overlapped entities through separate key features, such as shape and color, associated with each entity. Similarly, the compound fault can be recognized and separated into multiple single faults by judging whether the typical characteristics of the corresponding single fault exist or not, also known as decoupling. Different solutions to the question of "how to separate these faults" give an appropriate principle for summarizing the taxonomy of the CFD methods, which is detailed in the following section.

B. TAXONOMY OF CFD METHODS

Even though CFD has attracted increasing attention from academic and industrial researchers, it is difficult to reach an absolute consensus on how to summarize the taxonomy of CFD methods. For example, Zhang *et al.* provided a categorization for the CFD methods and relevant algorithms and thought that these methods generally fall into three categories: analytical model-based approaches, qualitative knowledge-based approaches, and data-driven-based approaches [10]. However, such a taxonomy provides little information about how the compound fault is recognized or decoupled and cannot summarize the published literature well.

Here, a well-designed taxonomy is proposed for the categorization of CFD methods according to the ways to solve the problem of how to separate these faults. Fig. 2 illustrates the proposed taxonomy for convenience, showing that the CFD methods can be divided into three groups: failure mechanism-based CFD, signal processing-based CFD, and artificial intelligence-based CFD.

Failure mechanism-based CFD refers to the methods that are trying to find the root cause that results in compound fault and to explain what, why, and how it happens, which can help us completely understand the compound fault mechanisms to come up with effective maintenance strategies for eliminating the compound failures that are causing downtime of machinery. One general way to achieve that is to establish a precise mathematical or dynamical model of machines using techniques like dynamic modeling and finite element or modal analysis. Failure mechanism-based CFD can provide solid fundamental theories for uncovering the physical laws behind the real symptoms and compound failure.

Signal processing-based CFD refers to the methods that are leveraging advanced signal processing technologies to extract fault-related information associated with different health statuses of machines from the monitoring compound fault signals, which allows experts to easily figure out which faults are coupled into the compound fault. An array of signal-processing algorithms has been published for CFD in the literature. The essence of these methods is to separate the compound faults by converting the compound fault signal in a way that engineers or experts can directly capture the discriminative and fault-related characteristics from the post-processing signals; thus, the compound fault can be decoupled into multiple single faults.

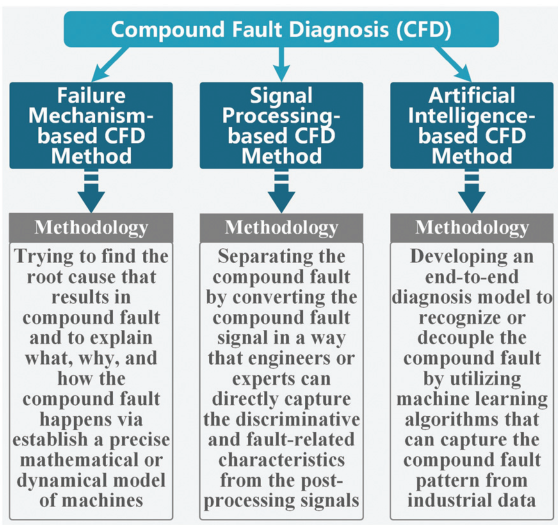

Fig. 2. Taxonomy of CFD methods.

Artificial intelligence-based CFD refers to intelligent CFD methods that focus on developing an end-to-end diagnosis model to recognize or decouple the compound fault by utilizing machine learning algorithms, such as shallow neural networks, deep learning, and transfer learning. The essence of these methods comes from the ability of artificial intelligence algorithms to capture the pattern or knowledge of compound faults from industrial data. Artificial intelligence-based CFD methods are being developed into two trends: a well-investigated way and an emerging-investigated way. The well-investigated way is to take the compound fault as an independent pattern of other single faults for fault classification, while the emerging-investigated way is to intelligently decouple the compound fault into multiple single faults by outputting the corresponding multiple labels.

It should be noticed that, although there may exist a few exceptions of past work (such as hybrid methods) that do not fall into the proposed taxonomy, the historical CFD methods are well-categorized following such taxonomy, and the prior work can be clearly discussed within such a framework.

III. APPLICATIONS FOR CFD OF ROTATING MACHINERY

CFD technologies have attracted tremendous attention from scholars and engineers who have made revolutionary breakthroughs in many applications over the past few decades. Generally, these technologies or applications may range in many ways, but they could be classified into the three categories introduced in the previous section. In this section, the general procedures of each type of CFD method, which can describe how the fault diagnosis can be implemented, are concluded to provide a convenient guide for helping readers grab the essence of the different methods. Thereafter, the historical publications, which focus on leveraging the corresponding CFD methods to deal with the problems encountered in the practical applications of fault diagnosis, are systematically summarized and discussed for providing a mature overview of CFD from different aspects.

A. APPLICATIONS OF FAILURE MECHANISM-BASED CFD METHOD

The failure mechanism-based CFD method aims to explore and reveal the correlation laws between the failure mechanism and the parameters of the established system model, which can help humans find the root causes that led to compound faults and their evolution process and can provide a theoretical understanding of CFD methods. The general procedures of the failure mechanism-based CFD method are summarized in Fig. 3. First, the system model is established to simulate the target machines, in which the key components are focused while other factors might be simplified. The ways to establish the system model typically include three classes, that is, mathematical model, phenomenological model, and dynamical model. Then, the system responses are simulated for different health conditions, such as the normal condition and the compound fault condition, using the established system model. In doing so, based on the generated vibration signals or order spectrums, CFD methods can be developed through system response analysis in which the system model is validated by comparing the experimental and simulated results.

Application examples of the failure mechanism-based CFD method include rolling bearings with compound faults [11–14], gear systems with multiple failures [15–17], and bearing-gear interaction systems [18,19]. Specifically, Patel *et al.* built a dynamic model to investigate the vibration response of deep groove ball bearings, where the single and multiple defects on inner and outer race surfaces are explored using both theoretical and experimental results [11]. To further investigate the multiple local defects on the same component, Patel *et al.* analyzed the vibrations in both time and frequency domains, in which the number of defects did not reflect in the frequency spectra but can be found in the time domain analysis [12]. Similarly, Zhang *et al.* established a four-degree-of-freedom dynamic model for rolling bearings with compound faults, in which the vibration characteristics of compound faults on the raceway and rolling element are analyzed. The relationship between the vibration response of the compound fault and three different working conditions is revealed based on the experimental validations [13]. Additionally, to reveal the

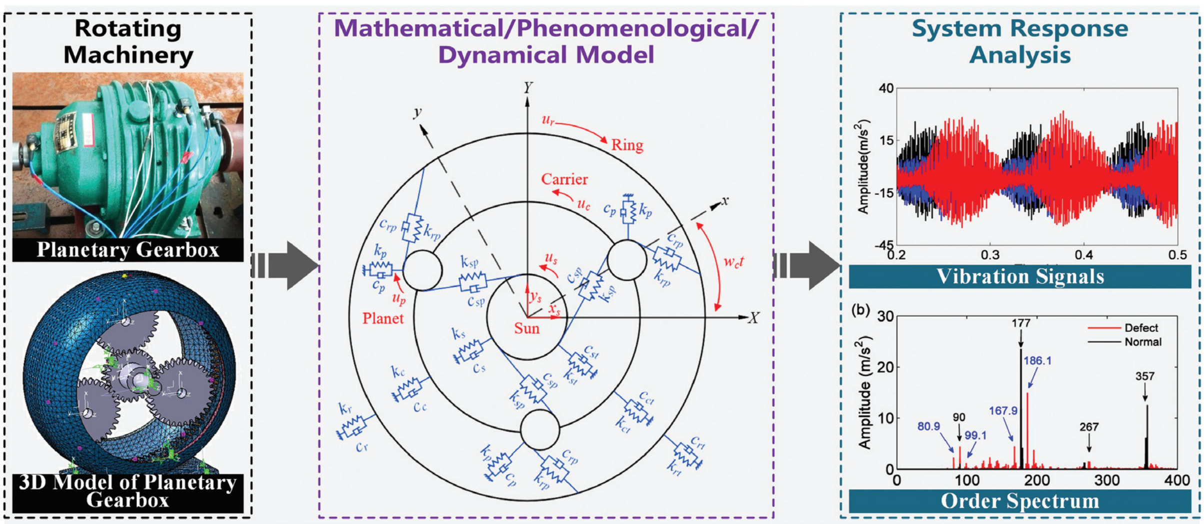

Fig. 3. General procedure of the failure mechanism-based CFD method.

correlation between single faults and compound faults, Yuan *et al*. used bearing practical kinematics and Hertz contact theory to construct the bearing-rotor dynamic model with a single fault on the inner and the outer race, respectively, and then a six-degree-of-freedom vibration model of rolling bearing with a compound fault of inner and outer race is modeled, in which a conclusion has been drawn that the Lempel-Ziv complexity measure can be regarded as a quantitative criterion to recognize the single and compound fault of bearings [14]. Apart from bearing compound fault, a four-degree-of-freedom dynamic model was constructed by Ma *et al*. for a gear system with local faults, and the dynamic model with tooth crack and spalling failure are used to explore the failure mechanism [15]. To explore multiple tooth cracks in spur gearboxes, Yang *et al*. investigated the mesh stiffness and the vibration response of three scenarios of multiple tooth cracks based on dynamic modeling, and then a method named crack-induced impulses was proposed to detect and locate the scenario of multiple tooth cracks [16]. A 20-degree-of-freedom lumped-parameter model was developed by Xue *et al*. to analyze the system response of planetary gear, in which gear defects on different components were introduced into the finite model to generate the failure vibration signals; thus, the failure mechanism of the planetary gear system was investigated by vibration response analysis [17]. Considering the more complex systems, Sawalhi *et al*. simulated and investigated the interactions between gears and bearings by combining the gear-bearing dynamic model, in which the inner and outer race faults of rolling bearings are discussed under the scenario with the gear interaction [18,19].

The experimental results presented in the publications illustrate that the methods mentioned above have been proven to be effective tools for CFD of rotating machinery and can provide the intuitive theoretical basis for fault diagnosis and health management. The CFD based on modeling and mechanism analysis has strong theoretical support in revealing the mechanism of fault generation, the essential correlation law between fault modes and their manifestations, and the interpretability of diagnosis results. However, with the complexity of mechanical equipment in structure, material, function, environment, and other factors, it is very difficult to build accurate and effective mechanism models for such a complex system, and the performance of failure mechanism-based CFD methods depends on the complexity of the target objects. These factors may be hindered the application of failure mechanism-based CFD methods in practical industries.

B. APPLICATIONS OF SIGNAL PROCESSING-BASED CFD METHOD

The signal processing-based CFD method aims to recognize the compound fault by extracting or separating the unique characteristics of the corresponding single faults from the compound fault signals, which helps engineers or experts intuitively decouple the compound fault into multiple single faults from the post-processing signals contained discriminative and fault-related characteristics. The general procedures of the signal processing-based CFD method are presented in Fig. 4. Generally, the compound fault signals are first captured from the target rotating machinery, which contains useful information associated with the health statuses of the machinery. However, when there exist multiple faults, the characteristics of each fault will be coupled together in a complex way, resulting in difficulties in extracting the discriminative features from the monitoring signals. To solve such problems, advanced signal processing algorithms, such as signal decomposition, signal deconvolution, blind signal processing (BSP), and sparse representation, are utilized to convert the compound fault signal into multiple parts where each part can represent a single fault coupled in the compound fault. Therefore, the compound fault can be detected and separated by observing or comparing the postprocessing signals. According to the exact signal processing algorithms being used, the applications of the signal processing-based CFD method are overviewed from the following four subcategories: signal decomposition-based method, signal deconvolution-based method, BSP-based method, and sparse representation-based method.

1) SIGNAL DECOMPOSITION-BASED METHODS. The essence of the signal decomposition-based method is to extract and separate the signal components from the compound fault signals. Signal decomposition-based methods are similar to pattern recognition that relied on feature engineering, in which the different components are expected to be separated. Scholars and researchers have proposed lots of successful methods for CFD, such as

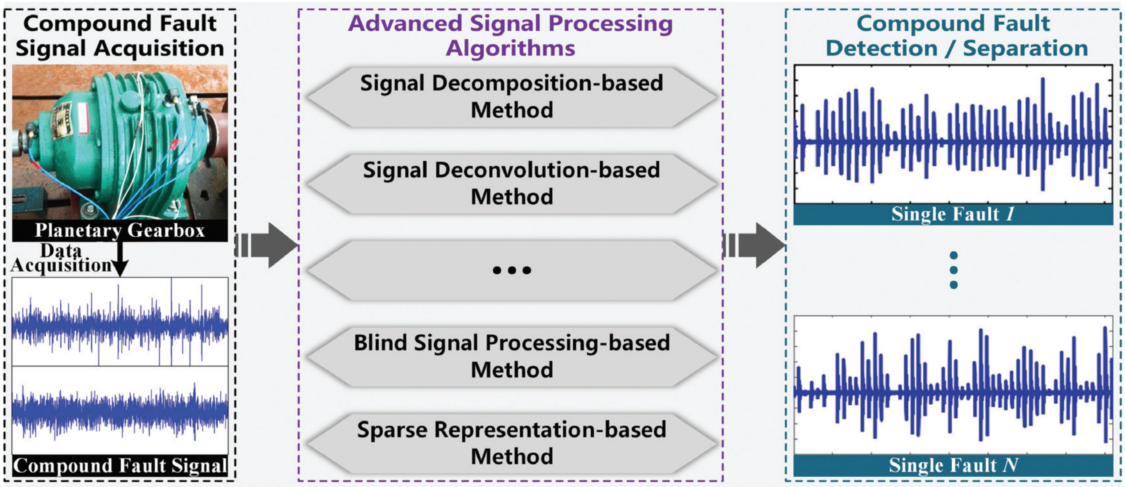

Fig. 4. General procedure of the signal processing-based CFD method.

wavelet transform (WT) [20–28], variational mode decomposition (VMD) [29–34], local mean decomposition (LMD) [35], singular spectrum decomposition (SSD) [36,37], symplectic geometry mode decomposition (SGMD) [38,39], and other methods [40–48]. The above methods have been widely applied in CFD of rotating machinery.

WT, also known as Wavelet Analysis, can be regarded as the presentation or projection of a signal using a set of basis functions (wavelets), bringing enormous applications including filtering, noise reduction, and feature extraction in the field of fault diagnosis. Peng *et al*. [49] and Yan *et al.* [50] systematically reviewed the WT and its variant algorithms for health condition monitoring and fault diagnosis in 2004 and 2014, respectively. As for CFD, Jiang *et al.* developed a method by combining empirical WT and chaotic oscillator (named EWTDO), which implements the CFD by the following steps: first, the compound fault signals are separated into different empirical models by empirical WT; second, a duffing oscillator which incorporates all single fault frequency is used to establish the fault isolator; finally, all the single faults can be recognized one by one by observing the chaotic motion from the Poincar mapping of the fault isolator outputs [20]. Ding utilized double impulsiveness measurement indicators to determine the lower–upper segment boundaries of empirical WT which can be further demodulated to detect the different single faults [21]. Different from the empirical WT, which uses the fixed basis functions, He *et al.* combined an adaptive redundant multiwavelet packet that can automatically select the sensitive frequency bands and Hilbert transform demodulation analysis to decouple the compound fault of two gearboxes [24]. An improved tunable Q-factor wavelet transform (TQWT) was proposed by Hu *et al.* to decompose the vibration signal, and the compound fault can be recognized by comparing the fault characteristic frequencies between the experimental results and theoretical values [27]. Although WT-based methods have many good properties ensuring the effectiveness in CFD, their decomposition performance of compound fault signals depends on the selected wavelet basis function.

VMD is also a prevalent algorithm to decompose the compound fault signal into multiple band-limited intrinsic mode functions. For example, Yan *et al.* combined the VMD with the 1.5-dimension envelope spectrum to detect the compound fault of rotating machinery, in which the compound fault signals are decomposed into several intrinsic mode components using VMD [29]. Wan *et al.* combined the fast spectrum kurtosis with the VMD to deal with the compound fault signals with weak single components [30]. Parameters of VMD, such as the penalty and the number of subcomponents, are significant for the decomposition results. Therefore, parameter-optimized VMD has also been investigated and applied in CFD for rotating machinery [32–34]. However, it is still lacking an effective solution for determining these parameters to ensure the diagnosis performance.

LMD, SSD, and SGMD are mode decomposition algorithms for nonstationary signals. Specifically, LMD is an adaptive mode decomposition algorithm that can decompose a compound fault signal into a set of mono-components that is, product function. Jay Lee *et al.* proposed a compound envelope construction method based on LMD for fault diagnosis of reciprocating compressors [35]. LMD has good performance in demodulating amplitude- and frequency-modulated signals, but it has limitations, such as end effects and mode mixing phenomenon. SSD is also an adaptive algorithm that can decompose nonlinear and nonstationary time signals in narrow-banded components. Wang *et al.* have proposed several methods based on SSD for composite fault diagnosis of gearboxes, which achieve higher decomposition accuracy and can overcome the modal mixing to some extent [36,37]. SGMD is a decomposition method that uses the symplectic geometry similarity transformation to reconstruct the mono-components with their corresponding eigenvectors. Pan *et al.* proposed a CFD method based on SGMD, in which the compound fault that is coupled by the bearing fault and gear fault are separated and recognized [38]. The above discussions show that the SSD and SGMD have been applied in CFD successfully. However, it is difficult to extract features of the weak single faults coupled in the compound fault signals since the SSD and SGMD have a strong ability of noise reduction and the weak fault information may be removed as noise. What's more, the pseudo-components are prone to be decomposed under strong noise environments.

Besides the aforementioned methods, there exist many other methods to make a CFD by combining the signal decomposition algorithm with other techniques. For instance, Tang *et al.* proposed a compound fault detection method with virtual multichannel signals in the angel domain and applied it to monitoring the rolling bearings under varying working conditions [43]. More details can be found in [40–48], which are not enumerated here.

2) SIGNAL DECONVOLUTION-BASED METHODS. The essence of the signal deconvolution-based method is to reverse the compound signal as single signals which are not coupled together. Signal deconvolution-based methods, such as minimum entropy deconvolution (MED) [51–55], maximum correlated kurtosis deconvolution (MCKD) [56–62], and cyclostationary blind deconvolution (CYCBD) [63], can enhance weak periodic features and suppress signal noise by constructing a comb filter, thus, have been proven to be an effective tool for separating compound fault with weak components.

MED is a technique that was developed for solving the deconvolution problem of a signal when it follows the convolutional form. Many examples show that the MED endows fault diagnosis methods with the ability to decouple compound faults. For example, Fan *et al.* proposed a CFD method for rolling bearings based on an improved MED adjustment and adaptive signal sparse decomposition, where the effectiveness of the proposed compound fault feature extraction is validated by both generated and experimental vibration signals of compound bearing fault [52]. A similar investigation for CFD of a wind turbine gearbox can be found in the work done by Feng *et al.* [54]. The advantage of the CFD methods based on MED is that it eliminates strong hypotheses over the components and only require the simplicity of the outputs.

Compared with MED, which only enhances single pulse components, MCKD-based methods have shown more powerful performance in CFD because MCKD can extract continuous periodic pulses. For example, Lyu *et al.* proposed an improved MCKD method for CFD of planetary gear by combining a quantum genetic algorithm (QGA), in which the single fault-related feature is extracted by the proposed method [58]. To deal with the problem that the periodic impulses may be contaminated by strong noise, Hong *et al.* developed a CFD method by combining customized balanced multiwavelets with adaptive MCKD, whose effectiveness is validated on the simulation and experimental data collected from the aero engine rotor [59]. The MCKD has been combined with other algorithms, such as spare representation and convolutional neural networks (CNNs), for implementing the CFD of rolling bearings, and the corresponding experiments also show that these methods can effectively separate the fault characteristic components and achieve good performance on CFD. Although the MCKD-based method has some metrics in extracting continuous periodic pulses, the feature extraction performance significantly relied on their parameters, such as filter length and deconvolution period.

CYCBD is a blind deconvolution algorithm that has been proven to be an effective tool for CFD because it can reconstruct periodic impulses from coupled fault signals. Applications can be found in [63], in which an improved adaptive CYCBD method was proposed by Sun *et al.* and applied for gearbox CFD under strong noise background. The CYCBD-based method provided an alternative way to extract weak shock faults from the compound fault signals.

Note that the CFD method based on signal deconvolution lacks effective evaluation criteria for the selection of key parameters, and the extracted features are easily affected by signal noise.

3) BSP-BASED METHODS. The essence of the BSP-based method is to separate unknown and independent source signals from mixed or composite signals. BSP, also known as bind signal separation (BSS), has been widely developed for solving the problem of CFD. Various effective algorithms have been proposed, such as independent component analysis (ICA) [64–67], sparse component analysis (SCA) [68–71], morphological component analysis (MCA) [72], and other methods [73,74]. These algorithms can separate the identification characteristics of each single fault source from the complex monitoring signals, to accurately evaluate the health conditions of rotating machinery.

ICA is a popular BSS algorithm for separating independent subcomponents from mixed signals, which is also suitable for dealing with the problems encountered in CFD. Viewing the CFD as a problem of underdetermined BSS for the vibration sources estimation, Wang *et al.* [64] and Tang *et al.* [65] proposed several CFD methods for rolling bearings by combining ICA with other mode decomposition algorithms, respectively. Experimental results showed that these methods are effective for compound fault separation and have better performance in separating strong noise signals than the signal decomposition methods [66,67].

To overcome the limitation of ICA that the estimation of source number must be done before the ICA which significantly increases the complexity of algorithms, SCA can avoid such estimation and solve the underdetermined problem by contrast, which has been widely applied in CFD. For example, Hao *et al.* have developed several CFD methods based on SCA and its variants algorithms [68–70]. The core steps of these methods are that the signal processing algorithm is first used to extract the sparse representation of the vibration signal and then put these representations into the SCA to obtain the precise source signal. Combining the SCA with other techniques, such as the morphological filtering of sin C function and density peak clustering, Xie *et al.* developed a method to effectively separate the composite faults of bearings [71].

Apart from the bearing compound faults, Yu *et al.* proposed an improved MCA method for the CFD of gearboxes under the scenario when a gear fault and a bearing fault occur at the same time [72], in which there are two different components (one is the meshing component caused by gear fault, the other one is the periodic impulse component caused by bearing fault) that coupled in the compound fault signal. Additionally, other methods, such as the null-space pursuit [73] and canonical correlation analysis [74], have also been applied in the CFD for aero-engine rolling element bearing by scholars.

Although BSP technology can deal with the difficulties encountered in decoupling compound faults of mechanical equipment to a certain extent, there are still problems, such as unsatisfactory performance and low reliability of results, when extracting or separating multiple fault sources due to the characteristics of nonlinear, high noise, and strong coupling of complex fault monitoring signals. Furthermore, the compound fault methods based on BSP have a high requirement on the channel numbers of the observed signal; that is, the number of sensors should meet the requirements of the algorithm, which may increase the cost of fault diagnosis.

4) SPARSE REPRESENTATION-BASED METHODS. The essence of the sparse representation-based method is to separate the compound faults by representing signals as linear combinations of a few atoms with a given overcomplete dictionary. The sparse representation-based method has been proven to be a prevalent tool in CFD due to its several advantages including different component matching, signal denoising, and signal separation without mode mixing. Generally, sparse representation theory mainly contains two aspects: overcomplete dictionary construction [74–80] and sparse coefficient solution [81–85].

The overcomplete dictionary construction is one of the key problems when we develop a CFD method. There are two ways to construct an overcomplete dictionary. The first one is the predefined analytic or static dictionaries. For example, Li *et al.* proposed a CFD method for gearboxes based on the multiple enhanced sparse decomposition algorithm, in which three subdictionaries are manually designed by considering the gearbox failure mechanism [78]. Meng *et al.* proposed a CFD method based on periodicity-weighted kurtosis sparse denoising and periodicity filtering, and the corresponding flowchart is shown in Fig. 5 [79]. It can be found that the impulse dictionary is constructed to obtain the sparse coefficients and fault types. The designed dictionaries typically have more explicit physical significance and good adaptability, but their limitation is that they may be out of work when processing unknown signals. The second one is the learning dictionary, which shows more advantages in feature extraction of the compound fault signals since it can adaptatively learn the atom library to match the target signals; thus, it is more effective to capture the fault-related features and has been widely applied in the field of fault diagnosis. Lin *et al.* proposed an effective CFD method based on an improved double-dictionary K-singular value decomposition (K-SVD) and applied it to rolling element bearings with inner and outer race defects [86]. Although these dictionary-based sparse representation methods have been successfully applied to separate the compound faults of rotating machinery, it is still a challenging problem of constructing a precise dictionary for CFD in practical industrial applications.

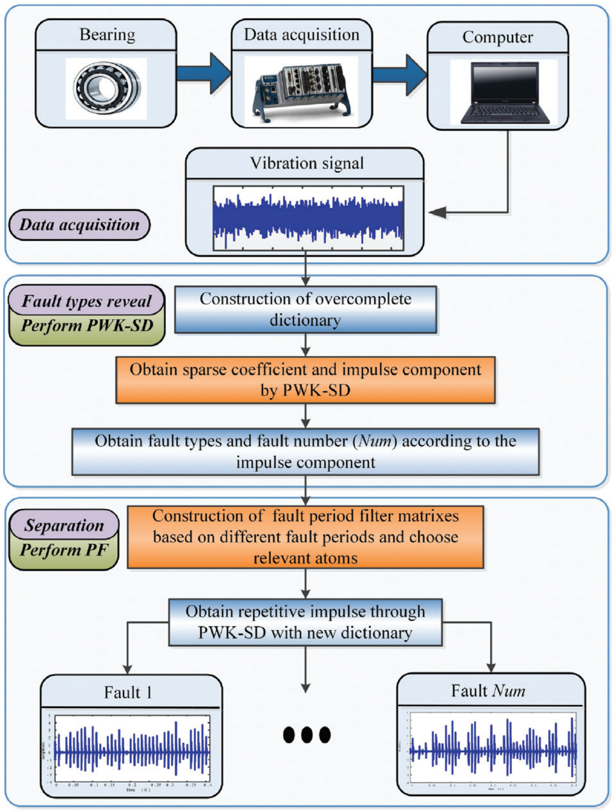

Fig. 5. Flowchart of the CFD method proposed in [79].

For sparse representation-based methods, solving the sparse coefficients is pivotal and has a significant influence on the performance of compound fault signal decomposition. Many approximate methods have been proposed for dealing with the sparse coefficient solution, among which convex relaxation optimization [81–83] and orthogonal matching pursuit (OMP) [84,85] have attracted the most attention in CFD. For instance, Huang *et al*. proposed a CFD method for gearboxes, in which a multi-source fidelity sparse representation algorithm was developed to convert the signal reconstruction problem into a multivariate sparse convex optimization problem [82]. Combining with the OMP algorithm, a multiple enhanced sparse representation method was proposed by Zhang *et al*. to reconstruct and identify each type of fault-induced feature for making the CFD of bearings [85].

Although the sparse representation-based methods have brought some successful breakthroughs in CFD, there is still a long way to go before they can be widely applied in more complex industrial scenarios. How to effectively use the sparse representation theory to mine the intrinsic characteristics of compound fault signals and realize the separation of more complex compound faults needs to be placed more effort in the future.

It should be highlighted that there are still many other CFD methods that have been developed based on signal processing algorithms that are not included in the four subcategories mentioned above, which will not be discussed here [87–90].

With the above overview and discussions, it can be found that the signal processing-based CFD methods usually extract the features of each independent fault component from the collected compound fault signals; thereby, they can achieve the purpose of decoupling and diagnosing compound faults. However, since they heavily depend on advanced signal processing methods and empirical knowledge of experts and cannot reveal the coupling law of compound fault signals, it is extremely difficult to distinguish and decouple the complex compound fault coupled by three or more faults, which limits their application in the practical maintenance of complex mechanical equipment.

C. APPLICATIONS OF ARTIFICIAL INTELLIGENCE-BASED CFD METHOD

The artificial intelligence-based CFD method aims to establish intelligent diagnosis models using machine learning algorithms, which can make a CFD in a pattern recognition way where the compound fault is regarded as an independent pattern for classification or can be decoupled into multiple single faults by outputting multiple corresponding single-fault labels. The general procedures of the artificial intelligence-based CFD methods are presented in Fig. 6. Specifically, the monitoring data/signals are first collected

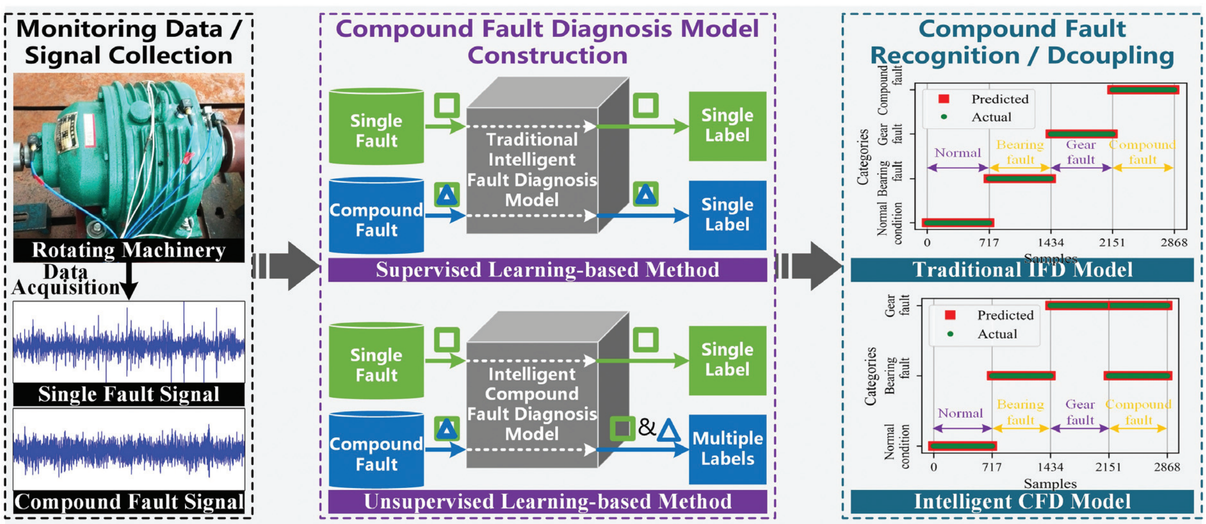

Fig. 6. General procedure of the artificial intelligence-based CFD method.

from the target rotating machinery, which is fundamental for training the intelligent CFD model since these methods typically recognize the compound fault by observing the given data. After the monitoring data has been collected, it is a critical step to construct the IFD model for compound fault by selecting the appropriate machine learning algorithms. Once the IFD model has been trained, it can be used to diagnose the compound fault in an end-to-end way, and the corresponding results can be obtained from the outputs of the IFD model. It is well-known that the collected data's quantity and quality significantly affect the fault diagnosis performance. Therefore, according to whether the labeled compound fault data are available or not during the process of model training, the artificial intelligence-based methods can be divided into two subcategories: supervised learning-based CFD method and unsupervised learning-based CFD method.

1) SUPERVISED LEARNING-BASED METHOD. The essence of the supervised learning-based method is to take the CFD as a pattern recognition problem for classification, which simply annotates the compound fault signal with another independent label to train the CFD model. That is to say, the supervised learning-based method is the same as the IFD method, which has been widely investigated in the past decade. For example, Li *et al.* gave a detailed introduction to the general procedure of the IFD method, as shown in Fig. 7 [3], in which the crucial step is the model construction. According to the artificial intelligence algorithms used to construct the diagnosis model, the supervised learning-based method can be further divided into two subcategories: shallow learning-based method, deep learning-based method, and multilabel learning-based method.

The shallow learning-based method typically utilizes the traditional machine learning algorithms, such as *k*-Nearest Neighbor (*k*-NN) [91–94], probabilistic graphical model (PGM) [95,96], support vector machine (SVM) [97–102], and artificial neural network [103–107], to construct the CFD model. For instance, Li and Yan *et al.* utilized signal processing algorithms including WT and Empirical model decomposition to extract the fault features from the nonstationary vibration signals, and then put them into the fuzzy *k*-NN to make a fault identification of gearbox with multiple faults [91]. Li *et al.* proposed a dimension-reduction algorithm, named Nearest and Farthest Distance Preserving Projection (NFDPP), based on the core idea of *k*-NN, of which the effectiveness is validated by a locomotive bearing dataset with compound faults [92]. Taking the non-Naïve Bayesian model (one paradigm of PGM) as the classifier, Asr *et al.* proposed a CFD method for automobile gearboxes [96]. As a popular pattern recognition algorithm, a series of SVM-based IFD methods were proposed by Chen *et al.* and applied to diagnose locomotive roller bearings with compound faults, in which the experimental results demonstrated that these methods are more effective and superior to other compared methods [100,101]. Similarly, Lei *et al.* proposed many hybrid IFD methods based on the Adaptive Neurofuzzy Inference System (ANFIS) and the Wavelet Neural Network, which improved the accuracy and reliability of fault diagnosis [103,104]. Wu *et al.* combined the ensemble extreme learning machine (ELM) network with binary classifiers to develop a CFD method for a two-stage gearbox. Through the above discussions, it can be found that, compared with the failure mechanism-based CFD method and the signal processing-based CFD method, the shallow learning-based CFD method can reduce the dependence on the experience and knowledge of experts, and show its advantages in compound fault classification. However, these methods based on the shallow learning algorithm suffer from the limitations of the poor abilities in feature learning and extraction.

Compared with the shallow learning-based method, the major difference is that the deep learning-based method aims to bridge the relationship between the health condition and the monitoring data in an end-to-end manner by utilizing hierarchical architectures to learn discriminative and fault-related representations from raw vibration signals. Various deep learning algorithms and its variant were developed by scholars for intelligent CFD, such as deep belief networks (DBNs) [108–112], sparse auto-encoder (SAE) [113–117], CNNs [118–126], long short-term memory (LSTM) neural networks [127], capsule networks (CapsNet) [128], and others [129]. Examples include but are not limited as follows: Shao *et al.* proposed various IFD methods for rolling bearings with compound faults, in which the DBNs algorithms are combined with other techniques like dual-tree complex wavelet packet and compressed sensing to enhance the performance of the proposed diagnosis model [108,109]; Xiang *et al.* proposed a multiple fault detection method based on DBNs and

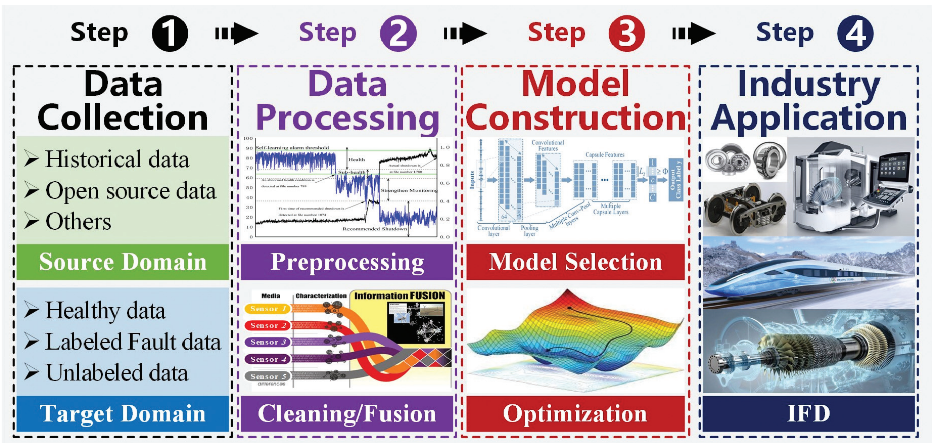

Fig. 7. General procedure of the intelligent fault diagnosis [3].

applied it for axial piston pumps [110]; Wang *et al*. proposed a CFD method for analog circuit system, in which multiple ELM with AE is used to automatically extract the fault-related representations from raw signals [117]; Combining with other algorithms, such as fast spectral kurtosis (FSK), SVMs, and data fusion techniques, CNNs have also been developed by many scholars and applied to CFD of rotating machinery [118–126]; Ma and Wang utilized several techniques including adaptive chirp model decomposition, Gini index fusion, and LSTM to develop a CFD method, which obtained a fault diagnosis model with better performance on the CFD of bearings [127]; Chen *et al.* proposed a fast robust CapsNet to detect the compound fault of ventilators and water pumps [128]. Although the methods reviewed above have brought many successful applications for rotating machinery, the obvious limitation is that these methods are simply viewed the compound fault as a unique fault that is unrelated to its corresponding single faults for fault classification. That is to say, the relationship between the compound fault and its corresponding single faults is overlooked in these methods.

To deal with such a limitation, the multilabel learning-based method was introduced to make a CFD with the multilabel outputting mechanism. Different from the shallow learning-based and deep-learning-based methods which annotate the compound fault samples with only one label, the multilabel learning-based method typically annotate the compound fault samples with two or more labels for supervised learning. Therefore, the compound fault can be decoupled into multiple single faults by the diagnosis model via outputting multiple labels. In recent years, the multilabel learning-based method has attracted increasing attention from related scholars, and various approaches have been proposed based on such ideas [130–135]. For instance, Huang *et al.* developed a CFD framework by combining deep CNNs with a multilabel classifier which can output single or multiple labels for a testing sample [130]. The essence of the multilabel classifier is to use the Sigmoid function to substitute the Softmax function as the activation function in the last classification layer, in doing so, the output probabilities of each classification neuron are independent, and the number of output labels can be determined by a customized principle. Following such insights, there are many similar methods that have been developed and investigated for the CFD of rotating machinery [131–135]. It can be concluded from the publications that the effectiveness of the CFD method based on multilabel learning has been validated. However, these methods have an obvious limitation: the training process of these models still relies on the labeled compound fault data, which is a difficult requirement for developing an effective solution in practical applications. It should also be highlighted that if the compound fault data are not available or not labeled, the supervised learning-based CFD method will be out of work and lose the ability of CFD.

2) UNSUPERVISED LEARNING-BASED METHOD. The essence of the unsupervised learning-based method is to decouple the compound fault into multiple single faults without the compound fault data, which means that the CFD model has the ability that it can leverage the knowledge learned from the single fault data to diagnose the compound fault. As illustrated in Fig. 8, the unsupervised learning-based method aims to imitate the phenomenon of humans that the overlapping entities can be easily separated into the corresponding entities by capturing the key features of each individual entity [3]. However, it is still a challenging task to implement such an "easy" task for artificial intelligence-based CFD methods. Fortunately, a few attempts have been made at implementing CFD under the scenario when the compound fault data are unavailable during the model training, and this research direction has attracted more and more attention from academic and industrial scholars [136–145].

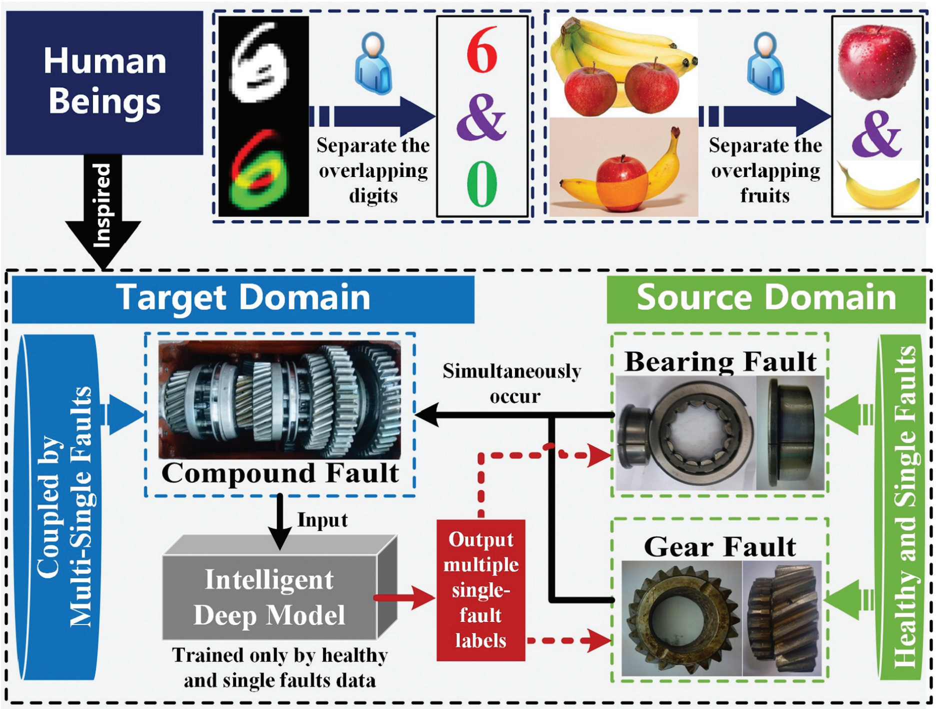

Fig. 8. Illustration of the motivation behind the compound fault decoupling [3].

The first successful attempt to decouple the compound fault only with the single fault data is the deep decoupling convolutional neural network (DDCNN), which is proposed by Huang *et al.* in 2018 [136]. In the DDCNN, several capsule layers are used to construct a decoupling classifier as a substitute for the traditional Softmax classifier, in which the compound fault samples can be decoupled into multiple single faults with multiple labels. The experiments carried out on an automobile transmission have demonstrated the effectiveness of CFD in an unsupervised manner. With the same goal, Dibaj *et al*. proposed a CFD method based on a hybrid fine-tuned VMD and CNN, which were applied to monitor a gearbox with compound faults [138]. Without the compound fault samples as training data, an intelligent CFD method based on zero-shot learning was proposed by Xing *et al*. and applied to detect the unseen compound fault of rotating machinery [139]. It can be drawn a conclusion from the above discussions that these methods have made a large step in CFD since they eliminate the dependency on the completeness of compound fault data. However, the diagnosis performance of the aforementioned methods still suffers from varying working conditions of rotating machinery, which has hindered the wide application in practical industry.

Inspired by the core idea of transfer learning which can enhance the generalization performance of AI models by learning the general knowledge from the different but related domains, Huang *et al*. further proposed several unsupervised intelligent CFD methods based on DTL algorithms, such as Transferable CapsNet (TCN) and deep adversarial capsule network (DACN), in which the generalization performance of CFD model has been significantly improved under varying or unseen working conditions [140,141]. Specifically, the core idea of TCN is to embed the transfer learning techniques into the CFD model (such as DDCNN), which has better generalization performance than DDCNN under varying working conditions [140]. Introducing the adversarial learning technique to train the CFD model, the DACN further endows the CFD model with the ability to intelligent decouple the compound fault across unseen working conditions [141]. More details about CFD based on DTL algorithms can be found in [3]. Besides the DTL-based algorithms, variants of other algorithms, such as Zero-shot Learning [142] and CapsNet [143], have also been developed for CFD of rotating machinery including bearings and rotate vector (RV) reducer.

Through the above discussions, in recent years, engineers and scholars have made various successful attempts and applications for CFD of rotating machinery based on artificial intelligent algorithms. With their efforts, the generalization performance of the CFD model has been significantly enhanced, and the dependency on the compound fault data completeness has also been eliminated by introducing unsupervised learning algorithms. However, it can be easily found from the historical publication that few works focus on the third compound fault introduced in Section II, Part A, that is, the compound fault occurred in a complex mechanical system with three or more single faults. Such aspects should be placed more effort by scholars in the future.

IV. FUTURE CHALLENGES AND OPPORTUNITIES

Despite the fact that, in the past decades, scholars and engineers from both academia and industry have brought enormous successful attempts for CFD of rotating machinery, how to make an accurate and reliable CFD remains a significant and challenging task in the field of fault diagnosis, especially in practical industry applications [144]. This is mainly because the historical CFD method lags far behind the demands of intelligent maintenance for complex machinery in the modern manufacturing industry, where the reliability and interpretability of the diagnosis model are placed more emphasis on. Therefore, after overviewing the state-of-the-art of implementing the CFD for rotating machinery, the challenges that need to be addressed and the opportunities that would be promising in CFD are outlined here for opening discussion.

A. FAILURE MECHANISM MODELING FOR COMPOUND FAULT OF COMPLEX MECHANICAL SYSTEMS

Understanding the physical failure mechanisms of compound fault occurrence constitutes the cornerstone of developing effective and accurate fault diagnosis solutions for rotating machinery. Admittedly, the failure mechanism-based CFD method overviewed in Section III, Part A is aiming at fulfilling this essential goal and also provides many basic rules or laws to reveal the root causes of the compound fault’s occurrence and evolution. Nevertheless, due to the complexity of mechanical equipment in structure, material, function, environment, and other factors, it is hard to establish a precise and reliable failure model for a complex mechanical system, let alone with a compound fault. As a result, the failure mechanism-based CFD method focuses less on the investigation of compound faults for complex mechanical systems. Therefore, it would be better to place more effort into failure mechanism modeling for the compound fault of complex mechanical systems. Fortunately, in recent years, the technology of the digital twin, which aims to build a dynamic virtual copy of a physical system, process, or environment that behaves identically to its real-world counterpart, has attracted growing attention from researchers in the related field [145]. We believe that, in the near future, it would be a promising tool to solve the problems mentioned above.

B. CAPACITY IMPROVEMENT OF SIGNAL PROCESSING ALGORITHM

The signal processing-based CFD method has been proven to be effective for separating and extracting the discriminative features of each independent fault component from the compound fault signals in many practical industry applications. However, it should be highlighted that there is no general signal processing algorithm that can be used for all the scenarios of CFD because all the signal processing methods aforementioned have their own advantages as well as disadvantages. Furthermore, the diagnosis results of the signal processing-based CFD method typically require the experts or engineers to make a post-decision based on case-dependent knowledge. Therefore, it is important and necessary to investigate more powerful signal processing algorithms and improve their capacity on all the aspects that are required in implementing the CFD, such as the performance of signal denoising, the detection accuracy of weak faults, and the decoupling ability of more complex compound fault signals. With the progress of sensing, measurement, and failure mechanism technologies, the signal processing-based method will remain one of the hot topics in the next decades.

C. INTERPRETABILITY OF INTELLIGENT CFD MODEL

It is an acknowledged truth that scholars have brought enormous and phenomenal breakthroughs for all aspects of CFD based on artificial intelligent algorithms. However, the bottleneck of the artificial intelligence-based CFD method is that these algorithms are perceived as an uninterpretable black technique, lack theoretical evidence to convince the machine's operators, and cannot work repeatedly and consistently in long-term manufacturing production. It is still difficult to understand or explain how and why the final decision is made by these intelligent models [146]. Importantly, in terms of the unsupervised learning-based CFD methods, few studies focus on the interpretability of how the compound fault can be decoupled into multiple single faults by only using the single fault data to train the CFD model. Thereby, lacking clear interpretability becomes the biggest obstacle to developing a CFD solution for practical application. Fortunately, researchers from both the field of computer science and the field of fault diagnosis have placed more effort into dealing with such challenges. How to design an interpretable CFD method and increase the transparency of its decision process is also one of the future trends in the field of fault diagnosis.

D. MORE INTELLIGENT CFD METHOD

Although the current IFD model can perform many challenging tasks, such as compound fault decoupling and emerging fault detection, and its performance is exceeded the human level in some aspects [147,148], there are still many abilities that the IFD model cannot perform. It is difficult for a majority of existing artificial intelligent algorithms to perform some tasks that are easy for humans, such as learning from a small set of instances, inferring or guessing for something, and implementing multitasks. Compared with algorithm intelligence, human intelligence is more reliable when encounters with high uncertainty and low predictability. Following such a perspective, we are confident that developing the CFD method with more adaptable and powerful intelligence will be an irresistible trend in the future, which will endow the intelligent model with the ability to imitate human beings' behaviors.

V. CONCLUSIONS

In this review article, a comprehensive survey on CFD for rotating machinery was conducted to provide a systematic guideline for potential readers and seasoned researchers. The importance of implementing CFD for rotating machinery was first highlighted at the beginning of this survey. The backgrounds of CFD including the related definitions and taxonomy of CFD were introduced to facilitate the following discussion on the state-of-the-art applications. The three groups of CFD applications, as well as their corresponding subcategories, were fully explored and discussed from the perspective of how the compound fault can be separated or decoupled, and their advantages and disadvantages were also concluded. Finally, the challenges and opportunities of implementing CFD, particularly for failure mechanism modeling for the compound fault of complex mechanical systems, capacity improvement of signal processing algorithm, interpretability of intelligent CFD model, and more intelligent CFD method, are outlined to open up some future research directions for researchers in the field of fault diagnosis.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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