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Fault Tracing Techniques for Mechanical Equipment: A Systematic Review

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Abstract: Fault tracing, a crucial part of fault diagnosis, is very important in reducing unexpected downtime and enhancing the availability of mechanical equipment. A thorough comprehension of diverse fault tracing techniques and their inherent characteristics is essential for choosing the most appropriate methods efficiently and accurately. This paper presents a comprehensive overview of research on fault tracing in mechanical equipment, using the Citespace software. It delves into the general research statue, tracing targets, methodologies, prevailing issues, and anticipated future challenges. The discussion revolves around two main tracing methods: data-based and knowledge-based. Each of these methods is introduced in detail, and comparisons are made of their respective pros and cons, as well as suitable application scenarios. Through a detailed review and summation presented in this paper, we strive to provide a systematic guide for implementing fault tracing techniques in industrial quality control. This endeavor is undertaken to offer practical insights for engineers seeking to bolster diagnostic systems, thereby improving the stability and quality of manufacturing processes.

Keywords: Fault tracing, Failure diagnosis, Citespace, Data-based method, Knowledge-based method.

1. Introduction

Mechanical equipment, being indispensable in sectors such as transportation, manufacturing, and aerospace, has seen its intelligence and automation levels escalating continuously. As application scenarios broaden, deepen, and become more stringent, along with increasing production demands, the operational conditions of this equipment become increasingly intricate, and operating hours become more concentrated. Given the intricate nature and strong coupling characteristics of mechanical equipment, even minor system defects can trigger faults, which are inevitable throughout the mechanical products' lifespan.

As a vital step in fault diagnosis, fault tracing aims to locate the root cause of faults and then provide guidance for maintenance. However, the intricate structure of machines, multiple interconnected physical fields during operation, and high functional coupling among components pose significant challenges in swiftly and precisely tracing faults for machinery. Statistics reveal that, in the process of diagnosing mechanical equipment faults, the time dedicated to fault tracing exceeds 80% of the entire diagnostic procedure [1].

When mechanical equipment experiences a failure, it invariably leads to unplanned downtime, causing significant production disruptions, property losses, and potentially catastrophic events like personnel injuries or fatalities. According to research, the industrial manufacturing sector experiences annual losses amounting to a staggering $50 billion due to such unexpected downtimes [2]. Furthermore, when equipment malfunctions, the inability to pinpoint the exact location and underlying cause of the failure hinders swift and effective repairs, leading to reduced equipment availability. Scientific fault tracing methods play a pivotal role in accurately locating and diagnosing the causes of faults. This ensures smooth and orderly production processes while significantly reducing repair cycles, thereby enhancing the utilization rate of mechanical equipment. Moreover, these methods contribute to minimizing maintenance costs and mitigating the losses associated with the impaired safe and proper operation of mechanical equipment.

Although fault tracing in mechanical equipment holds significant theoretical and engineering application value, a comprehensive review of the existing literature in this field remains elusive. There are only a few review articles related

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to fault diagnosis and fault detection on similar topics. In this paper, we adopt a broad definition of fault diagnosis, treating it as an overarching process that encompasses the entire workflow from initial abnormal detection to root cause identification. Within this framework, fault detection and fault tracing constitute two essential and sequential stages. Fault detection is the first stage, usually focusing on real-time monitoring of equipment operation to confirm the presence of a fault in a timely manner. It serves primarily as the basis for fault warning and for initiating the subsequent diagnostic procedure, but it cannot reveal the specific nature or cause of the fault. Fault tracing is the subsequent stage, which builds on the information obtained through fault detection and the intermediate characterization of the fault (such as its mode and location). It goes beyond identifying fault symptoms and aims directly at locating and analyzing the root cause, with a particular emphasis on revealing the physical mechanism of fault occurrence. Through fault tracing, the root cause of equipment failure can be accurately identified, thus providing strong support for equipment repair and prevention. The relations among them can be concluded as Fig.1 shows.

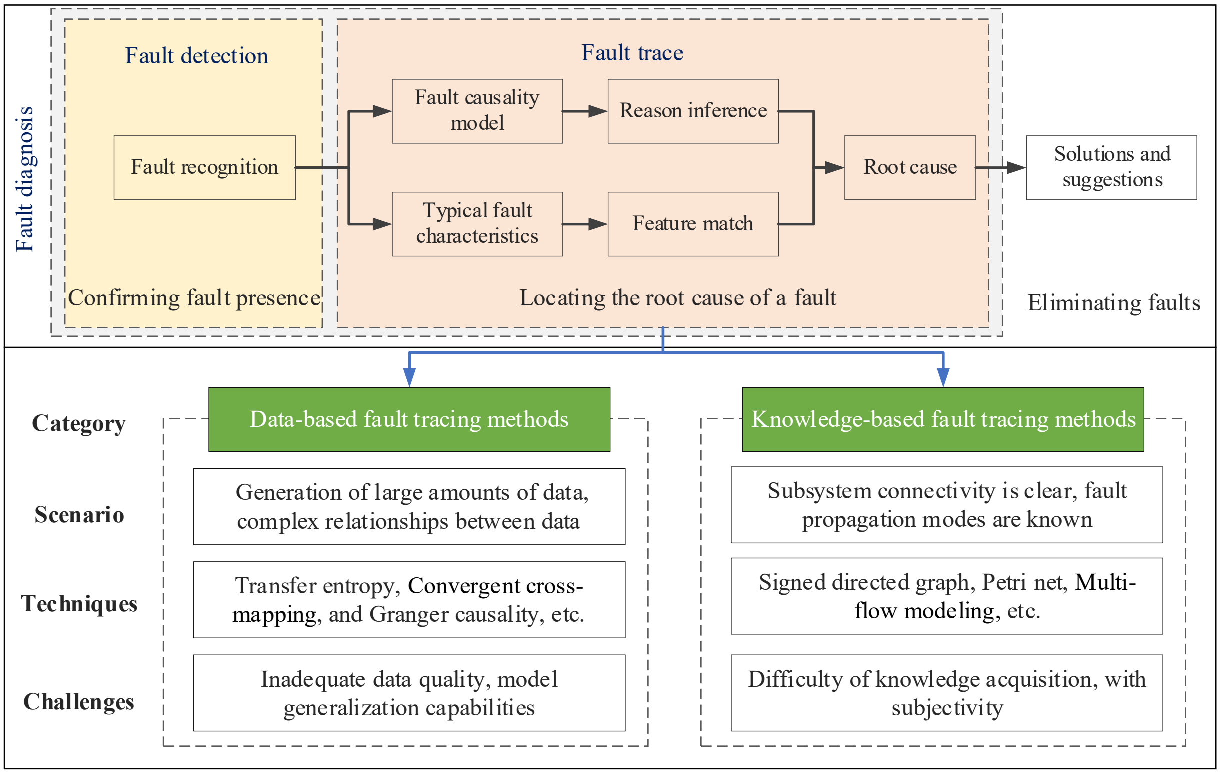

Fig. 1 Overview of fault tracing in mechanical equipment

To offer a comprehensive grasp of the advancements in fault tracing for mechanical equipment, this paper initially presents an overview of fault tracing in mechanical equipment based on Citespace. It proceeds to delve into the fundamental theories and methodologies pertaining to fault tracing in mechanical equipment, followed by a comparative analysis that highlights the strengths and weaknesses of diverse tracing methods. Finally, based on the current research landscape, it identifies the challenges and difficulties encountered in fault tracing for mechanical equipment and outlines potential avenues for future research. The contributions of the proposed work are included as below:

1) This review provides a comprehensive overview and in-depth analysis about fault tracing of mechanical systems based on Citespace.

2) It systematically introduces the basic overview and methods of fault tracing of general mechanical equipment, and compares the merits and shortcomings of different approaches.

3) Based on the current research status, the hotspots and difficult challenges that may be faced in future mechanical equipment fault traceability are summarized for future research.

2. Basic overview of fault tracing in mechanical equipment

To delve into the developmental trajectory of fault tracing in mechanical equipment, we conducted a visual analysis

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of the pertinent literature using CiteSpace software. The scope of our search encompassed the Web of Science Core Collection, focusing on articles published within the recent 18 years, from 2008 to 2025. The search query was specifically designed to capture articles discussing fault tracing and its related terminologies, encompassing TS=((“failure trac*”) OR (“fault trac*”) OR (“fault root cause trac*”) OR (fault trac*)) OR TS=(failure trac*). We narrowed our search to include only research papers and review papers, ensuring the relevance and quality of the retrieved documents. After carefully screening and eliminating any irrelevant literature, we ended up with a total of 288 relevant documents. These documents provide a rich and diverse dataset for our analysis, enabling us to gain insights into the evolving trends and patterns in fault tracing research for complex mechanical equipment. By employing CiteSpace’s visual analysis capabilities, we aim to gain a clear understanding of the key research themes, evolving trends, and collaborations within the field of fault tracing in complex mechanical equipment. This analysis will not only reveal the current state of the art but also identify potential gaps and future directions for research in this critical area.

Fig.2 displays a comprehensive co-occurrence network of keywords that reflects the key themes and relationships within the field of fault tracing in complex mechanical equipment. The size of each node is proportional to the frequency of keyword occurrences, indicating the significance and popularity of a particular term. The color of the connections between keywords represents the publication time of the associated literature, providing a temporal perspective on the development of these ideas. Keywords such as "Fault diagnosis", "Order tracking", "Signal", "Fault detection", "Vibration", "Empirical mode decomposition (EMD) ", "Feature extraction", "Model", and "Rolling element bearings" stand out as having higher frequencies, indicating their central role in the field. These terms not only reflect the core activities and techniques involved in fault tracing but also highlight the focus areas of current research. Connecting these keywords, it becomes apparent that the typical process for fault tracing involves signal acquisition, feature extraction, and tracking or modeling to achieve traceability. This process involves the analysis of signals generated by the mechanical equipment to detect anomalies or faults. Feature extraction techniques are then employed to identify relevant characteristics from these signals, which are subsequently used for fault diagnosis or tracking. Modeling approaches can also be utilized to predict and monitor the behavior of the equipment, allowing for proactive fault management. Empirical mode decomposition (EMD) is a frequently mentioned technique for decomposing vibration signals. This method is effective in extracting meaningful information from complex signals, making it a valuable tool for fault diagnosis. The high frequency of this keyword suggests that it has become a standard approach in the field.

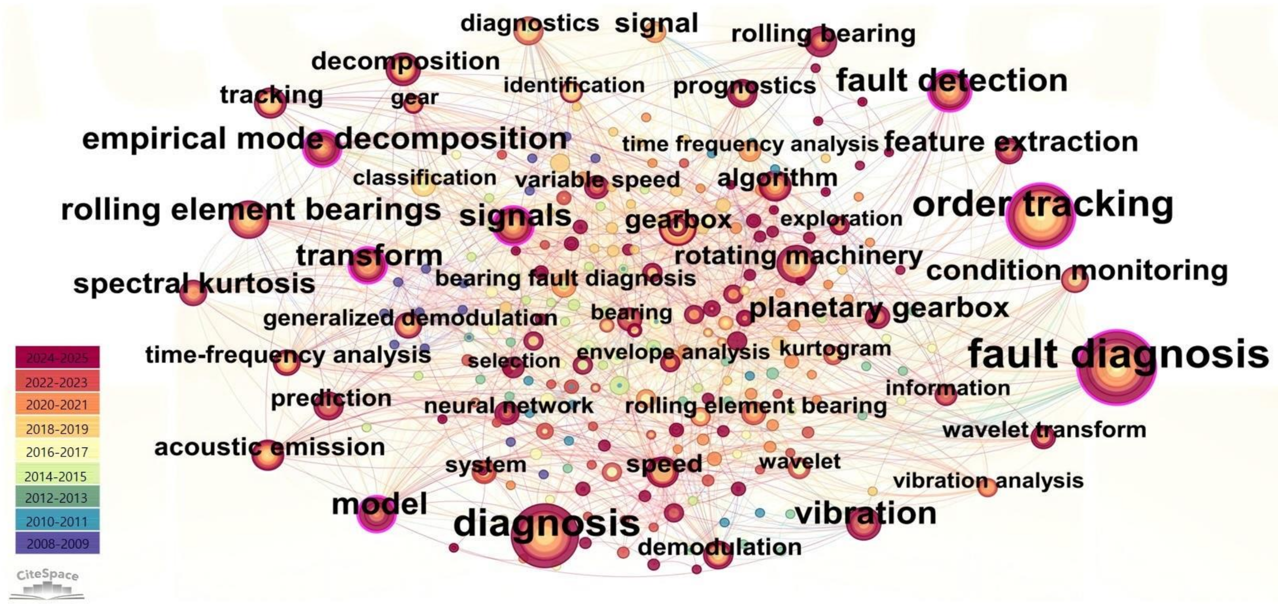

Fig. 2 Keyword network co-occurrence diagram

Moving on to Fig.3, the cluster diagram provides a more structured overview of the thematic areas within fault tracing research. Different colored blocks represent clusters of keywords that share similar themes or research topics. The corresponding text labels indicate the names assigned to each cluster, reflecting the main topics they include. Table 1

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summarizes the key information for the top four themes identified in the cluster diagram. These themes represent the most significant and active areas of research within the field of fault tracing in complex mechanical equipment. They range from dynamic modeling techniques that simulate and analyze the behavior of mechanical systems to wavelet transformations and artificial neural networks that process and interpret fault-related signals. It is noteworthy that while there is significant research on fault tracing methods such as dynamic modeling, wavelet transformations, and artificial neural networks, there seems to be limited research on causal relationship tracing methods. This gap indicates a potential area for future exploration and development, as understanding the causal relationships between faults and their underlying causes is crucial for effective fault management and prevention.

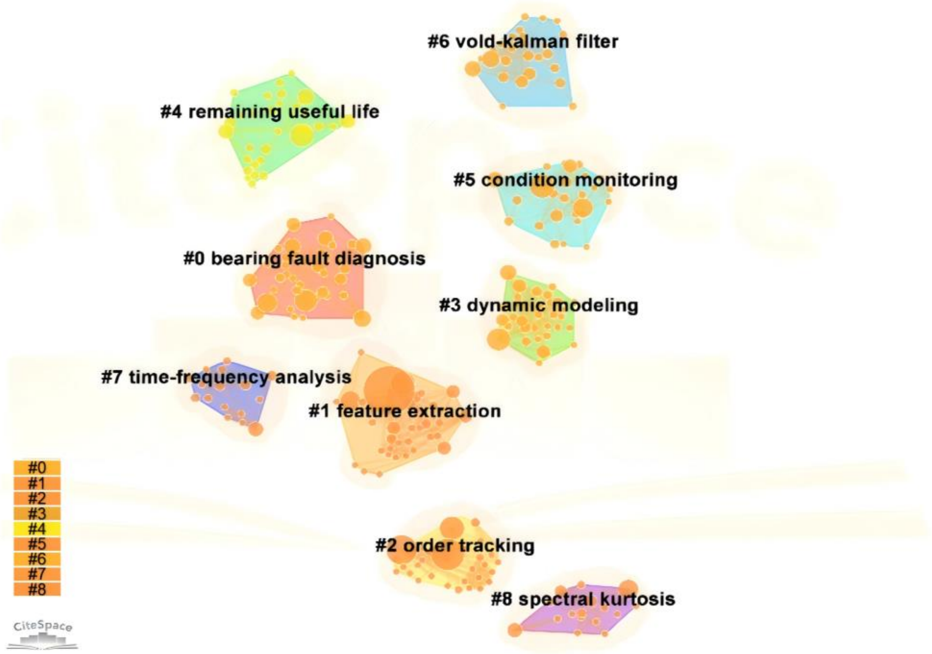

Fig. 3 Keyword clustering diagram

Table 1 Keyword clustering metrics information table

Group number	Clustering themes	Related keywords
1	Bearing fault diagnosis	Decomposition; tracking; transform; generalized demodulation; planetary gearbox
2	Order tracking	Neural network; wavelet; empirical mode decomposition; identification; classification
3	Dynamic modeling	Vibration analysis; speed; system; rolling element bearing; faults
4	Remaining useful life	Model; optimization; deep learning; prediction

Fig.4 shows the timeline of literature co-citations, highlighting the main clusters such as #0 bearing fault diagnosis, #4 remaining useful life, #5 condition monitoring, and #6 vold-kalman filter, which have consistently produced publications since 2010. These clusters include many highly respected articles, indicated by their large node diameters. Notably, the most recent literature has made many connections with these four key clusters, showing that there is a strong research focus that is closely linked to these areas. Furthermore, the second-largest cluster, #2 feature extraction, exhibits an earlier publication timeline, averaging around 2010. This important phase of feature extraction includes numerous valuable articles, serving as the cornerstone for subsequent noteworthy advancements in the realm of mechanical fault tracing.

To delve deeper into the intricate collaborative relationships among authors within this domain and illustrate the micro-level structure of the academic community, we constructed an author collaboration network. Our analysis focused on authors who have published a significant amount of work and made notable recent achievements, as shown in Fig.5. Notably, 237 authors in this field have formed 263 partnerships, with the most productive authors and their collaborators grouping into four relatively expansive subnetworks. Prominent authors such as Peng Zhike from Ningxia University

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(previously affiliated with Shanghai Jiao Tong University until 2022), Wang Dong from Shanghai Jiao Tong University, Chen Shiqian from Southwest Jiaotong University, and Liang Ming from the University of Ottawa stand out for their high publication frequency and profound research outputs. Collaborative networks encompassing authors like He Qingbo from Shanghai Jiao Tong University, Peng Zhongxiao, and Borghesani, Pietro from the University of New South Wales, Yan Tongtong from Shanghai Jiao Tong University, Wang Yi from Chongqing University, Chen Shiqian from Southwest Jiaotong University, and Chen Xuefeng from Xi'an Jiaotong University have yielded numerous novel outcomes in recent years. Additionally, collaborative efforts involving authors such as Randall, Robert B from the University of New South Wales, Liang Ming from the University of Ottawa, Cao Hongrui from Xi'an Jiaotong University, Guo Yu from Kunming University of Science and Technology, and Zhang Wenming from Shanghai Jiao Tong University have also generated abundant research outputs, although with fewer recent breakthroughs in this field. Table 2 presents a list of authors who have published the most in this domain. Their research has exerted a significant impact, and their methodologies and perspectives deserve careful consideration, serving as invaluable references for future research.

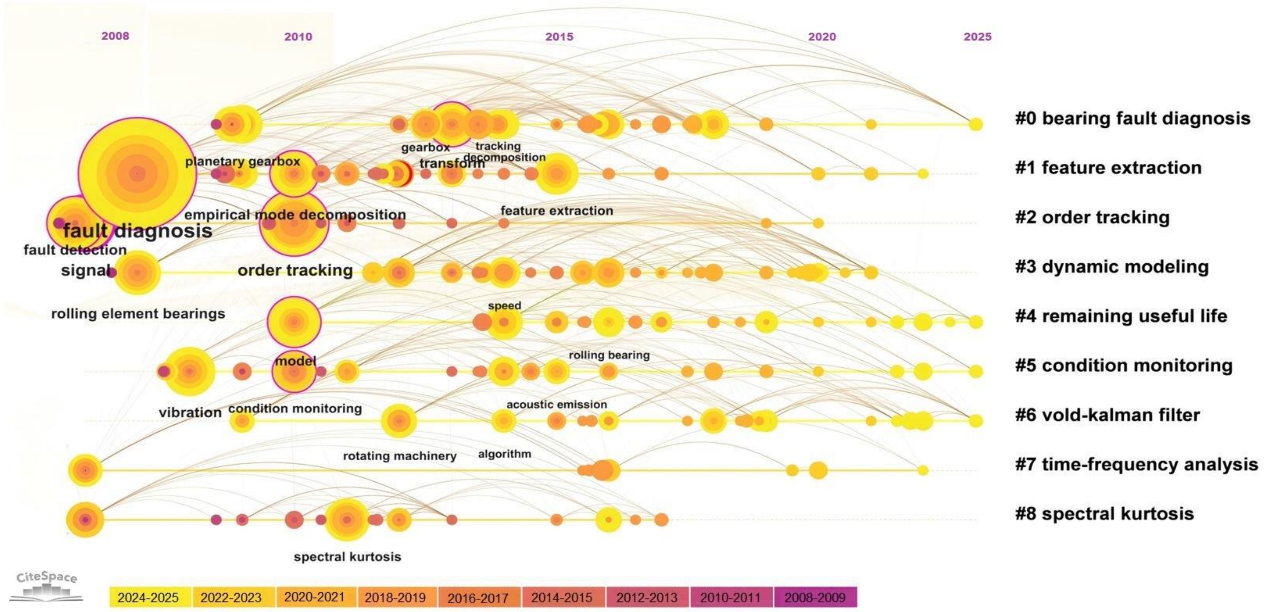

Fig. 4 Timeline of co-citation network clustering

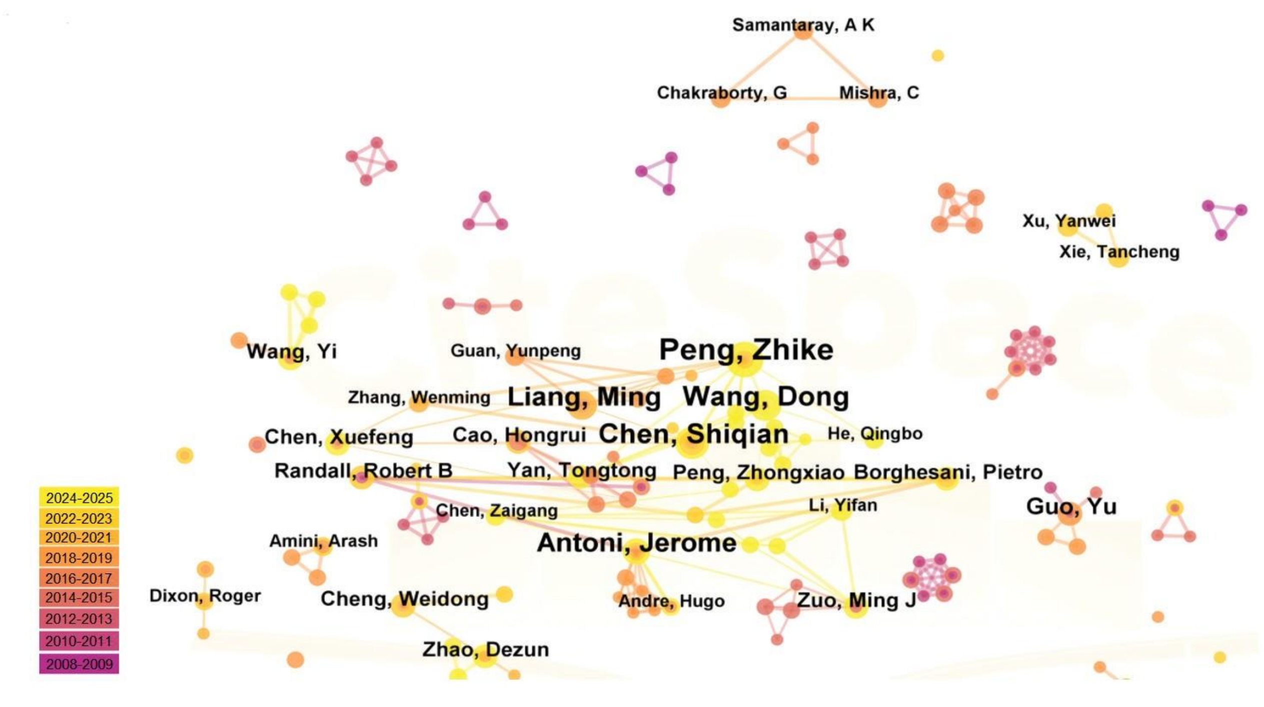

Fig. 5 Network of author collaboration

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The exploration of international cooperation and collaboration among research institutions in the fault tracing domain has indeed revealed interesting patterns. Through the analysis of cooperation networks between countries or regions and research institutions, we have gained valuable insights. As Fig.6 illustrates, the engagement of 43 countries or regions in fault tracing research is quite extensive, with 53 collaboration connections established. Among the top 12 countries or regions ranked by publication volume, China (Mainland) stands out as the most collaborative, with ties to 9 countries or regions. This suggests that China (Mainland) is not only a prolific producer of research in this field but also an important partner in promoting international collaborations. In contrast, the Taiwan (China) region appears to have a more limited collaboration scope, exclusively collaborating with China (Mainland). This could be due to various factors, including geographical proximity, cultural similarities, or policy considerations. India, on the other hand, lacks collaboration with other countries, which might indicate a need for greater outreach and engagement in international research partnerships. Australia, Italy, and other countries have demonstrated a broad collaboration scope, with 7 countries or regions, indicating their active participation in international research networks, as demonstrated in Table 3. This breadth of collaboration is likely to enhance their research capabilities and impact in the fault tracing domain. Furthermore, the emergence of three distinct subnetworks centered on China (Mainland), Australia, and England is noteworthy. These subnetworks represent clusters of collaboration that are likely to drive innovation and knowledge exchange in the field. The subnetwork with China (Mainland) at its core includes countries like France, the United States, Germany, and Canada, indicating its status as a hub for international research collaboration. The observations highlighted in this analysis not only underscore the leading position of China (Mainland) in collaborative research but also reveal the varying degrees of collaboration among different countries and regions. These insights can inform future strategies for enhancing international cooperation and collaboration in the fault tracing domain, leading to more impactful and innovative research outcomes.

Table 2 Publications and co-operation information of the main authors

Number of articles issued	Authors	Institutions	Number of co-operations
10	Peng Zhike	Ningxia University	8
8	Chen Shiqian	Southwest Jiaotong University	8
8	Wang Dong	Shanghai Jiao Tong University	8
7	Liang Ming	University of Ottawa	7
7	Antoni jerome	University of Lyon	8
5	Guo Yu	Kunming University of Science & Technology	4
4	Wang Yi	Chongqing University	4
4	Peng Zhongxiao	The University of New South Wales	5
4	Borghesani Pietro	The University of New South Wales	4
4	Chen Xuefeng	Xi'an Jiaotong University	6
4	Yan Tongtong	Shanghai Jiao Tong University	5
4	Randall Robert B	The University of New South Wales	4

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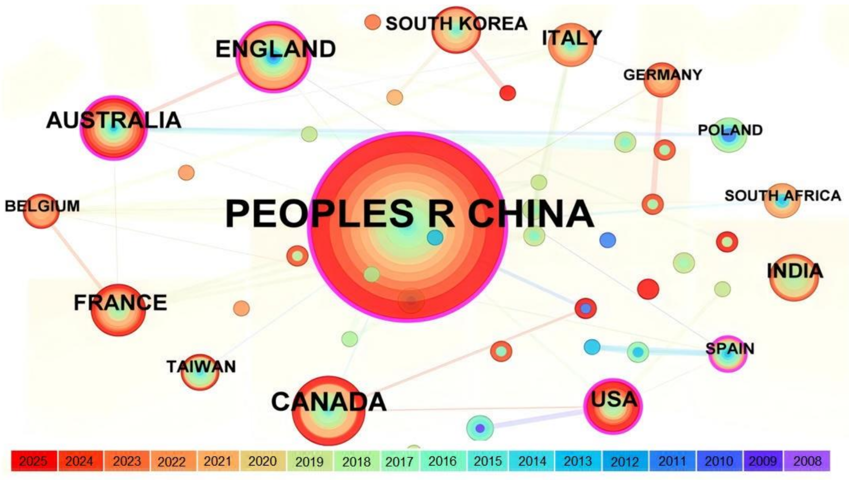

Countries	Centrality
China	0.24
England	0.11
Australia	0.18
USA	0.13
Italy	0.07
Belgium	0.10
Spain	0.16

Fig. 6 Network of national cooperation

To delve deeper into the realm of international cooperation and collaboration among research institutions in the fault tracing domain, Fig.7 offers a comprehensive collaboration network among 250 institutions, generating 209 collaboration connections. Prominent institutions such as Xi'an Jiaotong University, Shanghai Jiao Tong University, Southwest Jiaotong University, and the University of New South Wales stand out as the most collaborative among the top 12 by publication volume. While the University of Alberta maintains a degree of research independence, it has nonetheless achieved noteworthy outcomes, as highlighted in Table 3. This institutional collaboration network not only highlights the top research institutions in this field but also explains their intricate working relationships. Two distinct subnetworks emerge: one centered on Xi'an Jiaotong University, encompassing other top institutions like Shanghai Jiao Tong University and Chongqing University; and another independent network led by the Indian Institute of Technology and its collaborating partners. These institutions have consistently published literature in recent years, solidifying their leading and influential positions within this domain.

Table 3 Cooperation among the top 12 countries or regions and research institutions

Number of articles issued	Countries or regions	Number of cooperating countries	Number of articles issued	Institutions	Number of cooperating institutions
155	China (Mainland)	9	19	Xi'an Jiaotong University	15
27	Canada	3	18	Shanghai Jiao Tong University	11
19	England	5	13	University of New South Wales	9
17	Australia	7	12	Southwest Jiaotong University	10
15	France	5	9	Indian Institute of Technology	3
14	USA	5	9	Chongqing University	7
12	India	0	8	University of Alberta	2
11	Italy	7	8	Beijing Jiaotong University	4
9	Korea	2	7	National Institute of Applied Sciences, Lyon	5
7	Taiwan(China)	1	7	University of Ottawa	5
6	Belgium	7	6	Kunming University of Science & Technology	3
6	Spain	5	6	Loughborough University	4

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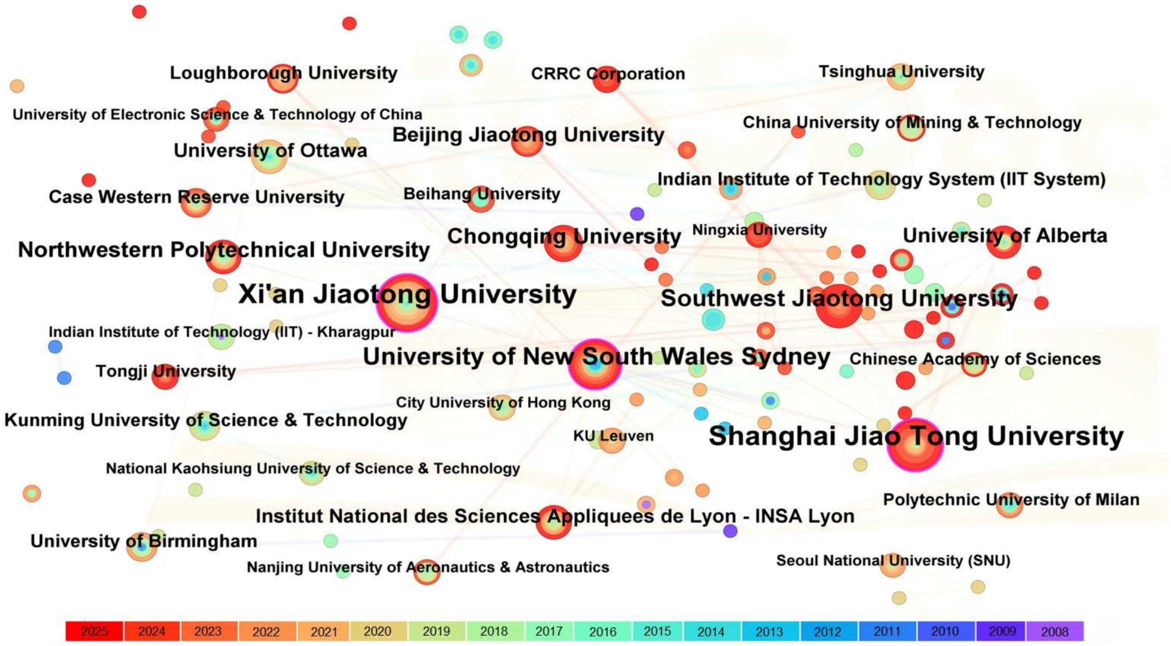

Fig. 7 Network of research institution cooperation

3. Fault tracing objects in mechanical equipment

Table 4 comprehensively outlines the objects and methods employed in fault tracing for complex mechanical equipment. Evidently, the scope of research in this domain is extensive, with a particular emphasis on aerospace, power generation, and other vital industries, where CNC machining holds a prominent position. Although fault tracing research now covers various areas and types of equipment important for the country's economy and defense, most of the work still concentrates on single parts of machinery. To achieve comprehensive fault tracing for entire complex mechanical systems, further research is imperative, rendering it a crucial area for future exploration.

Table 4 Objects and methods for fault tracing of complex mechanical equipment

Industry categories	Research objects	Research methods and models
Aviation and aerospace	Generators[3, 4], drones[5], aircraft power systems[6], engine lubrication systems[7]	Symbolic directed graphs for cloud models[3], knowledge graph[5, 6, 8-10], fault color map[4], jaccard correlation coefficient method, and neural network[7]
Power generation industry	Power equipment[11-13], wind turbine units[14], nuclear main pumps[15], power dispatch systems[16],metering devices[17], thermal power plant [18]	Petri nets[11, 12], Neural network models[13], BP neural networks[14], probability model algorithms[15], information difference graph models[16], deep information network models[17], principal component analysis model [18]
Automobile	Engines[10], motor bearings[19]	Neural network[10], digital twin[19]
Railway and marine transportation	High-speed trains[8, 20], marine engines[9], cargo ships[21]	Granger and fault propagation models[20], graph neural networks [9], probability density estimation multivariable causality models[21],
CNC machining	CNC rotary tables[22], hydraulic systems[23], CNC lathes[24-26]	Bayesian network models[22], fault tree analysis[23, 27], layered fault propagation directed graphs[24], fault propagation structure model [26]
Metallurgical industry	Metallurgy equipment[28], asynchronous motors[29]	Causal effect estimation learning models[28], deep bidirectional long short-term memory network[29]
Weaponry and equipment	Launch vehicles[30], loading machines[30], missiles[31], tank	Fault trees[30], Petri nets[30], bayesian networks[22, 31], variational mode decomposition and scattered entropy[32]

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	planetary gearboxes[32]	
General components	Roller bearings[33, 34], parallel axis gears[35], planetary gear reducer[24]	K-means clustering algorithms[33], visual graph amplitude entropy[34], in-situ measurement analysis methods and kurtosis algorithms[35], binary decision diagrams[24]

4. Fault tracing methods in mechanical equipment

The precision and effectiveness of fault tracing in mechanical equipment largely hinge on the methodologies employed for the purpose. The current methods employed in fault tracing can be broadly classified into two categories: data-based and knowledge-based. Data-based approaches hinge on real-time monitoring and a thorough analysis of historical data, whereas knowledge-based techniques rely heavily on the expertise and experience of domain experts. In practical applications, the selection of an appropriate fault tracing method depends on various factors, including the intricacy of the issue, the availability and quality of data, as well as the accessibility of domain experts. A integrated approach, integrating both data-based and knowledge-based techniques, often yields the most comprehensive and efficient tracing of potential fault origins in mechanical equipment.

4.1. Data-based fault tracing methods

Data-based fault tracing methods explore the causal relationships embedded in the operational data generated by mechanical equipment. The procedure begins with acquiring monitoring data, followed by preprocessing steps such as denoising, resampling, and normalization. Relevant features are then extracted from the time, frequency, and time-frequency domains to capture fault signatures. Core causal inference techniques such as transfer entropy and Granger causality are applied to quantify the information flow or causal strength between variables. Based on these pairwise causal relationships, a causal network or directed propagation graph is constructed. The root cause is then obtained by tracing backward from the detected fault node to the node with no incoming causal links. The overall procedure is illustrated in Fig. 8.

The main advantage of data-based methods lies in their flexibility and convenience. They neither rely on comprehensive expert knowledge nor require the construction of physical models, which has earned them widespread recognition in industry. Lucke et al. [36] conducted a rigorous classification of data-driven fault tracing techniques. Based on the employed Root Cause Analysis (RCA) strategies, they categorized these methods into four distinct types: univariate methods, time delay estimation methods, time-domain prediction methods, and frequency-domain prediction methods.

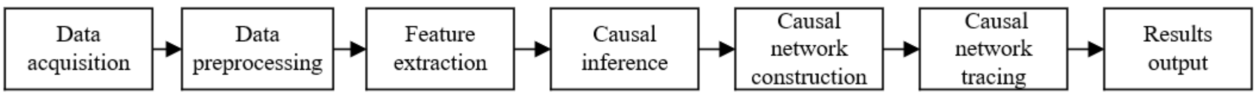

Fig. 8 Procedure of data-based fault tracing methods

Univariate methods presume that the characteristics of any process variable vary in accordance with its proximity to the corresponding root variable and process variable. Consequently, this attribute is leveraged to arrange the distances between the root and process variables in a distinct order. The Nonlinearity Index (NLI) stands as one of the more straightforward univariate tracing techniques, solely requiring the assessment of the nonlinearity degree of a single variable to ascertain the proximity to the fault source. The greater the distance from the fault source, the lesser the nonlinearity degree exhibited by the univariate. Uddin et al. [37] introduced a nonlinearity index to quantify the nonlinear characteristics of control systems, thereby validating the reliability of this approach. Tapioca et al. [38] established the theory of nonlinearity indices, serving as a metric for comprehending and quantifying the nonlinearity of aircraft under specific operational conditions, successfully implementing it in a nonlin ear pitch-yaw aircraft model. Maroua et al. [39] proposed a method using univariate statistical control charts to detect and diagnose crack faults in bevel gears by analyzing vibration signals. The results demonstrated that the proposed method was highly effective, as it quickly identified all different crack lengths at an early stage.

Delay estimation methods leverage the temporal lags of process variables to determine the sequence of faults, thereby interpreting the root causes of malfunctions. Among the commonly utilized techniques for delay estimation and tracing are the Cross-Correlation Function (CCF)[40-42], Dynamic Time Warping Causality Index (DCI)[44], and K Nearest Neighbours (KNN)[45]. Wang et al. [40] studied the compound faults of rolling bearing based on the CCF of envelope signal of vibration signals and 1D local binary pattern. Yu et al. [41] proposed a comprehensive approach that integrates information fusion, wavelet transform, Singular Value Decomposition (SVD), and cross-correlation functions. This method efficiently extracts composite fault features from inter-shaft bearings, accurately identifying fault types based on comprehensive gearbox vibration signals. Yang [44] developed a dynamic delay analysis approach that enables the statistical examination of temporal lags in process variables, achieving dynamic delay acquisition through historical data analysis. Joshuva et al. [45] employed K Nearest Neighbours (KNN) for feature classification in wind turbine blades, achieving noteworthy results in discriminating various blade fault conditions.

Time-domain-based prediction methods predict the occurrence of future phenomena in a time series based on the analysis of past phenomena in another time series, thereby establishing causal relationships. Depending on the definition of predictability within the time series, various prediction techniques are employed, including Transfer Entropy (TE) [47-49], Granger Causality (GC) [50-52], and Convergent Cross-Mapping (CCM)[53-56]. Lindner et al. [47] examined the oscillatory fault tracing problem, comparing the strengths and weaknesses of TE causality analysis and GC. Wang et al. [49] used an improved symbolic transfer entropy method to construct a directed-weighted information network, tracing fault propagation pathways by quantifying the information flow among system nodes. By quantifying metrics such as tracing accuracy, they laid the foundation for enhancing tracing efficiency. Huang et al. [50] proposed a nonlinear multivariate Lasso Granger method for fault propagation analysis in manufacturing processes. Chen et al. [51] developed a multivariate Granger causality analysis method that improved GC’s handling of nonlinear problems and enhanced its capacity to analyze multiple oscillation sources. Tian et al. [53] introduced a causal inference network grounded in the CCM method, enabling the tracing and analysis of nonlinear industrial processes. Scholars have widely applied the CCM method to intricate industrial sectors. Cheng et al. [54] addressing anomalies in chemical plant equipment, proposed a CCM method incorporating temporal characteristics and a dimension selection approach based on the Akaike Information Criterion. Zhao et al. [55] proposed a tracing method for complex industrial processes centered on a single model. This method utilizes an improved CCM approach to eliminate disturbances, accurately distinguishing relative causal changes between normal and fault states. This addresses the redundancy associated with fault diagnosis modeling and significantly reduces the complexity of fault tracing.

In contrast to time-domain analysis, which necessitates the examination of the entire power spectrum of the target object, frequency-domain analysis specifically concentrates on distinct frequencies during the operational process of the predictive object. Wang et al. [57] proposed a hybrid fault diagnosis method for high-speed wire rod finishing mills that integrates expert experience with data-driven techniques, utilizing improved frequency domain analysis for feature extraction. Xv et al. [60] proposed a novel blind fault separation and extraction technique for detecting bearing faults without prior knowledge. The method combines a 1/3-binary tree filter strategy and squared envelope spectrum autocorrelation to blindly estimate fault frequencies. Zhang et al. [61] developed a ground-based fault detection method for wind turbine planet bearings by analyzing modulation sidebands and demodulation spectra in generator current signals, successfully identifying outer race, inner race, and rolling element faults. Addressing the perennial challenge of measurement deviation or drift in sensors after prolonged usage, Li et al. [62] harnessed the power of neural networks to delve into the frequency-domain feature data of individual sensor signals. They proposed an innovative artificial intelligence diagnostic method, grounded in wavelet neural networks, and successfully applied it to sensor fault diagnosis in multi-sensor systems.

Table 5 presents comparisons of the primary current data-based methods of fault tracing for mechanical equipment.

4.2. Knowledge-based fault tracing methods

Knowledge-based fault tracing methods capture the causal relationships between process variables or events through causal diagrams or expert insights. Based on this, a causal reasoning framework is then constructed to trace the root cause of a malfunction. The process begins with the offline construction of a system knowledge model, such as a fault tree or a

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signed directed graph. This model encodes the causal structure of the system using expert experience, and historical failure records. When a fault is detected and its symptom (type, location, and severity) is recognized, this information is fed into the model. Reasoning is then performed, either forward to predict possible consequences or backward to search for underlying causes. The pre-defined causal chains are traversed to match the observed symptom and produce a root-cause hypothesis. This hypothesis is then checked against available data or expert judgement to confirm its validity. Once verified, the root cause is determined. The overall procedure is illustrated in Fig. 9.

Depending on the nature of the fault tracing subject, these techniques can be divided into two categories, those targeting fault events and those targeting fault variables. The former applies to systems with a clear sequence of events and causal relationships, while the latter is more suitable for monitoring and diagnosing faulty variables in complex systems and equipment. Methods focused on fault events include Fault Tree Analysis (FTA) [65-75], Failure Mode and Effects Analysis (FMEA) [76-80], Petri Net (PN) [81-82], et al. [83-84]. Methods aimed at fault variables include Signed Directed Graph (SDG) [85-88], Multi-flow Modeling (MFM) [89-91], et al.

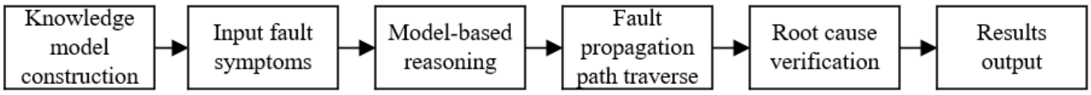

Fig. 9 Procedure of knowledge-based fault tracing methods

4.2.1. Fault tracing methods for fault events

Fault tracing for fault events mainly focuses on tracing and analyzing the fault event itself and its occurrence process, and determining the root cause of the fault by establishing the logical relationship and time sequence between the events. This method is applicable to systems with a clear sequence of events and cause-and-effect relationships, such as mechanical systems and electromechanical systems. FTA employs deductive reasoning, considering fault events as the focal points of analysis. It systematically delves into the potential causes of faults by tracing the causal logic relationships from the topmost level down. Chen et al. [23] applied FTA with interval rough number scoring and Dempster-Shafer theory to evaluate the possible failure cause in hydraulic systems of CNC machine tools. Aiming at the challenges of failure data scarcity and complex causal relationships of Maritime autonomous surface ships, Li et al. [65] developed a hybrid method of combing FTA and fuzzy Bayesian network to conduct the collision risk assessment. Luo et al. [66] conducted concurrent FMEA and FTA analyses on the feed system of a CNC machine tool, identifying crucial factors contributing to system faults and offering practical improvement suggestions. Long et al. [67] proposed an interpretable fault diagnosis model for aerospace equipment by integrating fuzzy fault tree analysis (FFTA) and an interval belief rule base. Zhou et al. [68] used interval models to represent the failure probabilities of each component, developing a system reliability analysis method grounded in FTA. Chen et al. [69] further enhanced the fault warning capabilities of CNC machine tools, introducing a standardized, comprehensive machine tool state monitoring approach that integrates energy considerations with FTA.

Given the significant uncertainty surrounding fault modes and causes in real-world complex mechanical equipment, scholars have introduced the fuzzy FTA method. Yin et al. [70] established the failure model of wind turbine gear transmission systems combining T-S fuzzy fault tree and Bayesian network. Guo et al. [71] further combined fuzzy mathematics, Markov models, and FTA frameworks to develop a dynamic FTA method utilizing a fuzzy Markov model. Wang et al. [72] developed a fuzzy FTA model for multi-state system with common cause failure, and demonstrated its effectiveness on an aircraft power system. Considering the lack of historical incident data of supply vessel collisions, Zong et al. [73] proposed a method for estimating the likelihood of supply vessel collision based on fuzzy FTA. Given the scarcity of component failure probabilities, Jiang et al. [74] proposed a method using the weakest n-dimensional t-criterion operation for fuzzy dynamic FTA, enabling the assessment of the system’s fuzzy reliability.

Recognizing the limitations of FTA in tracing the root causes of mechanical equipment failures, scholars have increasingly turned to FMEA for effective traceability, either standalone or in combination. Xiao et al. [76] introduced an FMEA method that considers risk elements and expert weights, enhancing the assessment of critical meta-action failure mode risks. Zhong et al. [77] addressed the challenge of handling fuzzy information in expert descriptions by proposing a novel FMEA approach based on the Fermat fuzzy weighted multi-head mean operator. Huang et al. [78] integrated FMEA analysis results with a multicolored matrix to construct a refined fault tree, facilitating the deduction of complex equipment failure root causes. Guste et al. [79] found out the primary causes of die attach machines by FMEA. To realize the diagnosis of most concurrent faults for electric isolation valves, Ai et al. [80] established a fault inference model based on FMEA. Additionally, some scholars have employed PN for precise fault localization. Sun et al. [81] combined intuitionistic fuzzy sets with fuzzy PN to develop an intuitionistic fuzzy fault PN model, addressing the significant uncertainty in gas turbine failures. Niu et al. [82] proposed an enhanced fault PN model capable of reliable fault isolation and diagnosis in multi-axis speed sensors. Furthermore, Yu et al. [83] developed a fault tracing method by combining causal ordering theory with the Ishikawa diagram. Given that multiple sources of information can provide more comprehensive insights, a multi-source fusion method based on expert experience was proposed [84].

4.2.2. Fault tracing methods for fault variables

Fault tracing for fault variables mainly focuses on monitoring and analyzing fault variables in a system to determine the cause and location of faults by comparing the differences between the fault variables and the normal state. This approach relies on sensors and measurement devices to collect data on fault variables in real time and extract fault characteristics through data analysis algorithms. The SDG causal analysis approach utilizes graphical symbols to establish fault propagation pathways, with nodes representing variables and directed line segments depicting causality logic connections. This method offers a robust and adaptable framework for expressing diverse systems, thus facilitating its widespread application in fault tracing for a range of mechanical devices. However, for large systems with numerous components and intricate fault factors, employing a forward reasoning engine for SDG model reasoning can result in complexities when combining fault causes. To tackle this challenge, Wang et al. [85] introduced an enhanced SDG-based fault diagnostic approach for complex systems. Ma et al. [86] developed an expert knowledge modeling software based on the SDG method, which integrates threshold and quality trend analysis to effectively diagnose incipient faults and reveal propagation paths for pressurized water reactor. Zhang et al. [3] addressed fault source identification and fault propagation in aircraft engines by developing a multi-operating condition fault diagnosis method utilizing cloud model SDG. Wang et al. [87] proposed a digital twin -enhanced SDG method for autoclave fault diagnosis, which improves diagnosis speed and resolution by using the digital twin to reduce potential fault paths and simplify inferences. Liu et al. [88] enhanced the SDG method through the integration of qualitative trend assessment and granularity calculation algorithms, significantly enhancing decision-making speed in tracing multiple fault causations.

In comparison to the SDG method, MFM offers a distinct advantage in identifying crucial system components and fault propagation paths. Reinartz et al. [89] introduced a methodology that integrates MFM to automate the generation of causal reasoning models. This approach is particularly effective in domains such as nuclear equipment, where it can create SDG diagrams automatically, significantly improving the accuracy of fault tracing. Peng et al. [90] proposed an integrated fault diagnosis method that combines principal component analysis and an MFM to enhance the accuracy and reliability of online fault diagnosis in nuclear power plants. Lin et al. [91] developed a model based on a multi-layer stochastic flow network to analyze failure propagation in high-speed train systems, incorporating load redistribution strategies to predict fault paths.

Knowledge-based methods exhibit distinct value and pose specific challenges during the modeling process of intricate mechanical equipment. The core of this method is rooted in articulating causal associations through meticulous knowledge manipulation and fashioning computer-recognizable and retrievable frameworks [92], such as symbolic directed graphs and rule-based models [93]. These models are good at summarizing specific operational experiences and profound insights inherent in complex equipment processes, ultimately offering a comprehensive comprehension of system behavior patterns. Nevertheless, compared to data-driven fault tracing techniques, knowledge-based approaches rely heavily on the precision of mechanical models and the completeness of rules made by experts.

Table 6 presents comparisons of the primary current knowledge-based methods of fault tracing for mechanical equipment.

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Table 5 Comparisons of data-based fault tracing methods

Categories	Criteria	Methods	Advantages	Disadvantages	Adapted scenarios
Univariate method	Single variable	Nonlinearity index[37-39]	Capture complex non-linear relationships	Complex calculations; Weak interpretability	Faults are well characterized and easy to identify from a single variable
Delay estimation method	Time delay between signals	Cross-correlation function [40- 43]	Easy to use and suitable for delayed analysis	Only for linear relationships	Fault propagation with a significant time delay
		Dynamic time warping causality index [44]	For data with inconsistent lengths	Complex calculations; Affected by noise	
		K nearest neighbors [45-46]	Adaptable without assuming data distribution	Noise sensitive; Computationally inefficient	
Time domain prediction method	Time series data	Transfer entropy [47, 49]	Adaptation to non-stationary data	Large amounts of data are required	Fault is preceded by a significant time trend or periodicity
		Granger causality [50-52]	Applicable to linear models	Captures only linear relationships; High smoothness requirements	
		Convergent cross-mapping [53-56]	Ability to detect non-linear causality	High data quality requirements	
Frequency domain prediction method	Frequency characteristics of signals	Spectrum analysis [57-59]	Intuitive and fast calculation speed	Unable to handle a non-stationary signal	Fault is clearly characterized in the frequency domain
		Envelope spectrum analysis [60, 61]	Sensitive to early failures	Parameter selection requires experience	
		Wavelet transform [62-64]	Suitable for a non-stationary signal	Complex calculations	

Table 6 Comparison of knowledge-based fault tracing methods

Categories	Criteria	Methods	Advantages	Disadvantages	Adapted scenarios
Fault events	Fault process and chain of events	Fault tree analysis [65-75]	Clearly structured for easy identification of the cause of system failure	Difficult to handle dynamic systems; Unable to capture concurrent failure	Fault events with clear causal relations
		Failure mode and effects analysis [76-80]	Easy identification of high-risk components; easy modeling of system reliability	Highly subjective; Difficult to apply to complex systems	
		Petri net [81-82]	Ability to characterize the concurrency and dynamics of a system	Complex model construction; High computational resource requirements	
Fault variables	Fault-related variables or parameters	Signed directed graph [85-88]	Visual representation of cause and effect relationships	Only able to handle static relationships in the system; Difficult to deal with complex interactions	Familiar with fault mechanism
		Multi-flow modeling [89-91]	Hierarchical and suitable for distributed analysis of multilevel systems	Data-dependent; Complex to model	

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5 Hotspots and challenges in fault tracing of mechanical equipment

5.1. Hotspots in fault tracing of mechanical equipment

Based on the comprehensive analysis provided, it is apparent that considerable experience and results have been gained in the ongoing research on fault tracing in mechanical equipment. In terms of the object of traceability, the research primarily concentrates on the key parts or components of mechanical equipment that are susceptible to failure, particularly bearings, gears, and simple rotor systems. Regarding the methods of fault tracing, enterprise technicians widely adopt classical methods such as FTA and FMEA, owing to their advantages of ease of operation and strong practical applicability.

In recent years, with the development of interchangeable networks, internet of things and other technologies, the monitoring and processing capacity of mechanical equipment operation data has been greatly improved. Artificial intelligence traceability methods based on data such as mechanical learning and deep learning are highly sought after and have become a hot spot in the current fault tracing research. At the same time, it is also the field with the most achievements in fault tracing and even fault diagnosis related research in the past five years. The related research mainly focuses on the optimization of fault data feature construction and prediction model.

Although deep learning methods can extract fault feature information from massive data for traceability, the interpretability of such methods is weak. On the other hand, as an important technology in the field of artificial intelligence, knowledge graph can display the reasoning and decision-making process through visualization methods. With the successful application of knowledge graph in search engines, knowledge graph-based fault tracing methods have gradually become an emerging point for fault tracing.

5.2. Challenges in fault tracing of mechanical equipment

Despite significant advancements in current fault tracing research, it still encounters several challenges when dealing with complex mechanical equipment faults:

(1) The current fault tracing objects are mostly components or simple mechanical systems, and there is less research on fault tracing for the whole machine or complex systems. In mechanical systems, the interaction between components is the root cause of failure. Compared with mechanical components, the whole machine of mechanical equipment consists of many subsystems, and there is a more complex coupling between the components. The system presents a multi-level, highly sub-linear characteristics. When tracing the fault of the whole machine, it is necessary to establish the interaction and dependence model between the various levels of the system. By employing techniques such as decoupling or dimensionality reduction, among others, researchers can systematically map the failure mode from the functional appearance of the entire machine down to the interactions between its components and parts. This layered approach helps find the root cause of the fault.

(2) Current research on mechanical product faults primarily focuses on inference methods, while neglecting the modeling technology associated with fault tracing. As is well known, fault tracing primarily involves two core aspects: the establishment of a traceability network and the inference of traceability methods based on this network. Among these, the establishment of fault tracing network serves as the foundation for fault tracing. The accuracy of the network model has a direct impact on the accuracy and efficiency of the fault tracing. Existing fault tracing networks are primarily constructed based on empirical methods, and the process involves numerous subjective factors, which can readily result the omission of potential causal relationships. For newly developed products, due to the lack of experience, such methods are even helpless. Therefore, there is a need to develop traceability methods with low dependence on experience. The mapping model between product failure modes and potential causes can be established based on the sufficient conditions for the achieving mechanical equipment functions and performances. On this basis, a fault traceability network can be constructed utilizing the mapping method to prevent the omission of potential failure causes.

(3) Currently, fault tracing is based on subjective information such as expert experience or using objective information such as sensor monitoring data and fault records to build inference models. There are few comprehensive reasoning methods that consider both subjective and objective information. As a matter of fact, the information about the

causes of mechanical equipment failures is usually scattered in the surrounding environment in multiple channels and forms, and each type of information reflects a certain side of the failure. The reasoning method of integrating multi-source failure cause information helps to understand the root cause of failure from multiple aspects. It can make up for the lack of one-sided information from a single channel and thus improve the accuracy of the traceability results. For example, knowledge graphs can be used to visualize the relations between expert knowledge and operation data to help identifying failure modes and causes. To enhance the credibility of diagnoses derived from analyzing monitoring signals with machine learning, expert feedback can be integrated to refine and adjust the model. Another scenario involves using mathematical models, built upon expert knowledge, to describe the normal operating state of the system and to identify potential faults by comparing actual signals with model predictions.

(4) In terms of changes in operating conditions, existing fault traceability methods tend to rely too heavily on static models or preset conditions. Many fault traceability analyses tend to look for the cause of failures under a single or static condition, ignoring the complexity of the impact of changing operating conditions on the equipment as a whole. A change in operating conditions may not cause an immediate failure, but it can have a cumulative effect in the system. Traditional traceability analyses often fail to identify these hidden risks that gradually accumulate, which in turn leads to inaccurate analysis results. A cumulative damage model should be established to consider the long-term effects of different operating conditions on equipment performance. By analyzing historical operating data, the fatigue and wear patterns of equipment under frequently changing conditions can be identified, thus enhancing the generalization ability of the traceability model.

(5) Multi-stage mechanical systems involve the collaborative operation of multiple subsystems, and failures or abnormal behavior in one subsystem may be transmitted to other subsystems through these coupling relationships, leading to system-level failures. However, traditional fault traceability analyses often focus excessively on individual components and ignore the complexity of the system as a unified entity. In multilevel systems, faults may propagate between subsystems in a nonlinear manner with complex propagation paths. The lack of a systematic understanding of the synergistic operation of multilevel systems makes it difficult to analyze fault propagation in depth, leading to difficulties in accurately locating the source of faults. A comprehensive systems engineering approach should be adopted to analyze the interactive effects in the multilevel mechanical system and identify the coupling points between the subsystems and their effects on fault propagation. The collaborative operation of the subsystems should be taken as the focus of the analysis, and the interaction and feedback mechanism between the systems should be emphasized.

6. Conclusions

This paper presents a comprehensive overview of the development of fault tracing in mechanical equipment, utilizing Citespace as a foundational tool. It introduces the landscape of fault tracing within mechanical equipment and systematically delineates the prevalent approaches employed in this field. Additionally, the paper outlines the applicable scenarios for these techniques based on their properties. According to the current research status, tracing faults in complex, multi-stage mechanical systems and systems with variable operational conditions poses significant challenges. Potential solutions may lie in the adoption of multi-source information fusion and system engineering methods. Besides, reliable causality modeling techniques are also worthy of investigation.

Competing interests

The authors declare that they have no competing interests.

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