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Review

Toward cognitive predictive maintenance: A survey of graph-based approaches

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ABSTRACT

Predictive Maintenance (PdM) has continually attracted interest from the manufacturing community due to its significant potential in reducing unexpected machine downtime and related cost. Much attention to existing PdM research has been paid to perceiving the fault, while the identification and estimation processes are affected by many factors. Many existing approaches have not been able to manage the existing knowledge effectively for reasoning the causal relationship of fault. Meanwhile, complete correlation analysis of identified faults and the corresponding root causes is often missing. To address this problem, graph-based approaches (GbA) with cognitive intelligence are proposed, because the GbA are superior in semantic causal inference, heterogeneous association, and visualized explanation. In addition, GbA can achieve promising performance on PdM's perception tasks by revealing the dependency relationship among parts/components of the equipment. However, despite its advantages, few papers discuss cognitive inference in PdM, let alone GbA. Aiming to fill this gap, this paper concentrates on GbA, and carries out a comprehensive survey organized by the sequential stages in PdM, i.e., anomaly detection, diagnosis, prognosis, and maintenance decision-making. Firstly, GbA and their corresponding graph construction methods are introduced. Secondly, the implementation strategies and instances of GbA in PdM are presented. Finally, challenges and future works toward cognitive PdM are proposed. It is hoped that this work can provide a fundamental basis for researchers and industrial practitioners in adopting GbA-based PdM, and initiate several future research directions to achieve the cognitive PdM.

1. Introduction

1.1. Predictive maintenance

Maintenance is an essential and significant part of manufacturing, which contains functional checks, services, and repairing or replacing necessary devices or equipment in manufacturing scenarios. In literature, the maintenance domain can be divided into three categories: reactive maintenance (RM), preventive maintenance (PM, also known as time-based maintenance), and predictive maintenance (PdM, which is extended from the condition-based maintenance) [1]. RM aims to repair or restore the operational state after the failure occurs, which leads to a severe lag and causes a higher repair cost. PM is to execute a maintenance schedule based on the time or the manufacturing process to keep the equipment in a healthy state, which may lead to unnecessary maintenance and extra costs. Compared with the above two kinds of maintenance strategies, PdM achieves the trade-off between them, which performs pre-failure intervention and monitors the healthy condition timely, responding more flexibly to the actual dynamics of the machines. In practice, PdM decreases the maintenance frequency as low as possible to avoid unexpected reactive maintenance and reduces the expenditures of conducting superfluous preventive maintenance. A vivid illustration of RM, PM, and PdM can be referred to Fig. 1. Generally, PdM includes anomaly detection, diagnosis, prognosis, and maintenance decision-making [2].

Recently, cognitive intelligence (also known as cognitive computing)

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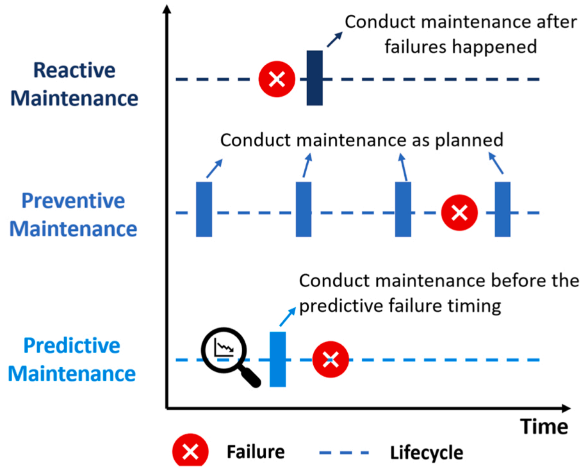

Fig. 1. Maintenance strategy of RM, PM, and PdM.

has attracted much attention in various domains due to its ability of perception (prediction) and explanation [3]. Cognitive intelligence originated from neuroscience, where it mentions the human brain contains two parts: the first part relates to distinguishment and determination; the second part relates to reasoning and explanation (Fig. 2). It aims to understand the presented information, interpret contextual meaning, and draw deductions through correlation analysis and causal inference. Therefore, cognitive PdM can be regarded as a combination of cognitive intelligence and PdM. The cognitive PdM not only occupies the same functions and characteristics as traditional PdM, but it can also explain the causality of the fault and reveal the risk of adjacent components, and mitigate the (upcoming) failure hierarchically.

Specifically, the potential risk of adjacent components can be revealed by correlation analysis based on the interpretable mechanical structure and multi-physics mechanism. In addition, the weight and statistical factor in correlation analysis can be served as the degree of impact. Meanwhile, it is noticed that a correlation relationship does not represent causality. For example, old equipment has loud noise, which does not necessarily mean that old equipment causes loud noise. One alternative explanation is that the old equipment is always along with old components, which may loose or abrasion. These old components lead to loud noise rather than the equipment's service time. Therefore, causal inference needs to satisfy the specific semantic basis.

1.2. Graph-based approaches for cognitive PdM

Many existing approaches have achieved cognitive intelligence [3] and implemented in various disciplines [4], while seldom of them applied in PdM. Graph-based approaches (GbA) are an effective pathway to achieving cognitive intelligence because they exploit and aggregate the relationship of events, features, samples, and equipment components through semantic associations. Compared with other

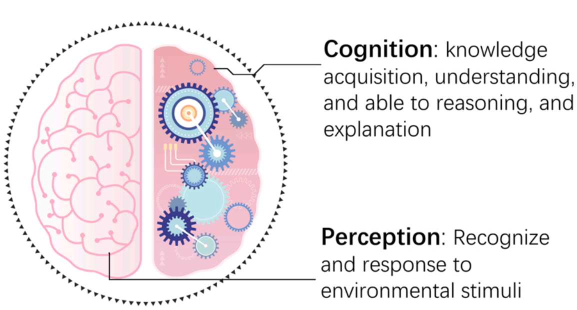

Fig. 2. Two aspects of cognitive intelligence.

methods, GbA have the following advantages:

Visualization: Visualization provides a graphical interface for managing and understanding complex data. Different kinds of nodes link together with the visual graph, which enables a multidimensional representation of data. In addition, visualization promotes the concise graph to reflect the miscellaneous knowledge, leading the engineer to understand the complex situation and conduct the corresponding plan in PdM. Furthermore, graph visualization includes different kinds of edges, revealing the causality for maintenance.

High-level representation: Graph contains entities, attributes, edges, and corresponding structures, of which the initial representation is the original information for the node-level, edge-level, and graph-level. Based on graph structure, the initial representation aggregates the neighboring information and then generate a high-level embedding, which integrated the information itself, the surrounding information, and its position in graph structure. The obtained high-level representation provides the hierarchical information, as the prior knowledge, benefiting PdM calculations.

Reasoning: Edges have pre-defined meaning in some graphs, representing logical and semantic relationships between nodes. Based on the significative edges and nodes, the missing edges can be deducted by the existing nodes' interaction by embedding-based methods or semantic methods. In addition, searching the path of two long-distance nodes reveals the correlation or causality of fault in PdM.

Propagation: Each node in graph has associated nodes that share similar characteristics to some degree. If one node is the searching result, then its adjacent nodes serves as the secondary result for reference. In addition, meticulous PdM requires holistic solutions to maintain the equipment hierarchically. Therefore, same-level nodes are integrated as a comprehensive and diverse solution.

Based on the above metrics, GbA can be a promising manner to achieve accurate perception, correlate, and causal analysis with graph aggregation and graphical explanation, towards the so-called cognitive PdM.

1.3. Limitations of existing studies

Over the past years, there are multiple review papers concentrated on different aspects in PdM. Due to the rapid development of data science recently, many researchers summarized data-driven approaches in PdM, especially in deep learning [2][5], and machine learning [6]. Apart from what has been mentioned above, model-based [7] and knowledge-based [8] approaches are also two mainstreams in PdM, which have also been summarized respectively. Furthermore, one of the main characteristics of cognitive PdM is reasoning (or causal inference). However, one work attempted to summarize the ontology approaches in PdM, while it just included four papers in reasoning section [9]. In addition to method-based taxonomy, some papers concluded PdM approaches for different usage scenarios. In macro level, some works have summarized the applications in PdM for different environments, such as smart factories [10], Internet of Things [11], and railway systems [12]. In micro-level, numerous research works had implemented different methods in PdM for instance cases, such as digital twins [13], motors [14], and semiconductors [15].

Although the above papers have provided exciting reviews in different fields in PdM, they have the following limitations: (1) Most of the papers analyzed the PdM approaches in diagnosis and prognosis, while PdM covers more than these two aspects, such as anomaly detection, and maintenance decision-making. (2) Previous review papers summarized PdM approaches based on data-driven taxonomy, such as deep learning and machine learning, or categorized by the usage scenarios, while no work looks from GbA perspectives. (3) Past review papers focused on the accuracy of different methods (perception), while failing to summarize the methods for fault explanations and traceability (cognition).

1.4. Objective

To address the above limitations, this paper conducts a comprehensive literature review regarding GbA in PdM under the cognitive intelligence framework to:

(1) Evaluate different GbA and various graph establishment manners of each approach.

(2) Compare the merit & demerit, perceive ability, cognitive ability, and application of different GbA for each stage in PdM, including anomaly detection, diagnosis, prognosis and maintenance decision-making.

(3) Summarize the challenges and difficulties of implementing GbA in practice and highlight the future development directions.

The rest of this paper is organized as follows: Section 2 describes the systematic literature review process and analyzes the selected items and trends in this field. Section 3 reviews relevant GbA. Section 4 summarizes the characteristics of various GbA along the different stages in PdM. Section 5 and Section 6 further discuss the existing challenges, and highlight the future perspectives, respectively.

2. Systematic literature review

2.1. Literature selection

The systematic literature selection process is illustrated in Fig. 3. The relevant publications are extracted from the Scopus and Web of Science (WoS) databases, owing to its broad coverage of the major peer-reviewed articles in academia. The search sentence was written as: “Topic= (graph OR semantic OR ontology) AND Topic= ("prognostic health management" OR ”predictive maintenance" OR “fault diagnosis"); Time Span: 2016–2022; Language: English”. After the first-round screening, 783 items from Scopus and 570 from WoS were found (accessed on March 52 022). Then, a second-round search was conducted, where only academic journals and conferences in the English version were included. Besides, the topics not within the field were excluded (e.g., optics, medical) to refine the existing papers, and 101 relevant items were extracted. Thirdly, a more detailed review was undertaken by reading the content and references of the items, excluding those methods without topological structure. Moreover, related papers found in the references will also be added. Finally, after more in-depth reading of those, a total of 91 items were selected as the foundation of this survey.

2.2. Statistical analysis of selected items

Fig. 4 (a) summarizes the number of publications by year based on the original searching result, of which indicated a prevailing concern recently. This can also be revealed by a recent Special Issue ‘Semantic Artificial Intelligence for Smart Manufacturing Automation’ in the journal of Robotics and Computer-Integrated Manufacturing in 2020[2] and ‘Industrial Knowledge Graph-enabled Cognitive Intelligence-Driven Mass Personalization’ in the journal Advanced Engineering Informatics in 2021.[3] Moreover, Fig. 4 (b) shows that major sources are published in the ‘IEEE Transactions on Instrumentation and Measurement’, ‘IEEE Access’, and ‘Advanced Engineering Informatics’. Other published papers are dispersed in various disciplines of journals, such as reliability (IEEE Transactions on Reliability, Reliability Engineering & System Safety), measurement (Measurement, Journal of the International Measurement Confederation), and manufacturing (Journal of Manufacturing Systems, Journal of Intelligent Manufacturing).

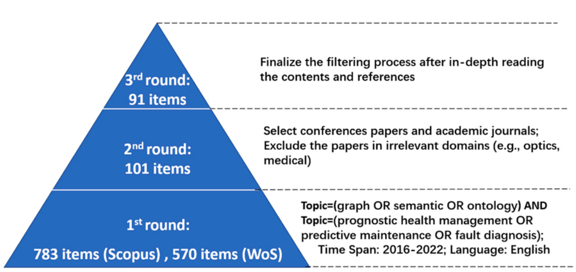

Fig. 3. The systematic literature selection process.

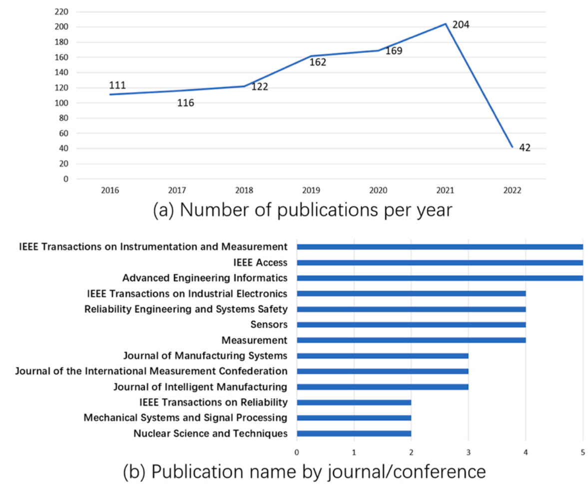

Fig. 4. The statistical analysis of the selected publications.

3. GbA for predictive maintenance

The following section introduces the four mainstream GbA in PdM domain: Graph neural network (GNN), Knowledge graph (KG), Bayesian network (BN), and Graph theoretic model (GTM). The theory and characteristics are summarized in Table 1.

3.1. Graph neural network

GNN relates to deep learning, which obtains high-level representation through aggregation (Fig. 5). The obtained representation (also known as an embedding) can be applied in node-level, edge-level, and graph-level downstream tasks. Meanwhile, GNN has been applied in many sectors, including chemistry [16], medicine [17], finance [18], etc.

Graph structure of GNN can be established based on the monitoring data, and there are three frequently-used methods: feature similarity, data point similarity, and equipment structure (Fig. 6). Feature similarity treats the features as nodes, and calculates the similarity between nodes to generate edges. Analogously, data point similarity uses data points as nodes (e.g., the subsample from the univariate or multivariate time series). Meanwhile, the equipment structure method indicates that graph construction follows the mechanical structure and mechanism, where components and parts serve as nodes.

Feature similarity-based graph construction: features-level construction is tailored for multivariate, where each feature is considered as

[2] https://www.sciencedirect.com/journal/robotics-and-computer-integrated-manufacturing/special-issue/10BP80M3M74

[3] https://www.journals.elsevier.com/advanced-engineering-informatics/call-for-papers/industrial-knowledge-graph-enabled-cognitive-intelligence-driven-mass-personalization

Table 1
The theory and characteristics of different GbA.

Approach	Theory	Characteristics
Graph neural network (GNN)	GNN is deep learning approach for graph-based tasks, aggregating through graph structure for high-level representation.	GNN performs data inference and deduction in graph form, benefiting node-level, edge-level, and graph-level tasks.
Knowledge graph (KG)	KG is constructed by pre-defined entities, edges, and corresponding attributes. Finding the satisfying results through semantic querying and reasoning.	Knowledge stored in graph database can be accessed and explored quickly. Besides, the semantic nodes and edges can be used for causal inference and association analysis.
Bayesian network (BN)	BN is a probabilistic graphical model, where the variables serve as nodes, and the conditional dependencies are described by the directed edges.	BN satisfies the local Markov property, stating a node is conditionally independent of its non-descendants given its parents.
Graph theoretic model (GTM)	Applies graph theoretic model to describe the operational processes or variables relationships to find the critical node, path, community, etc.	Only need traditional graph structure for deduction and inference.

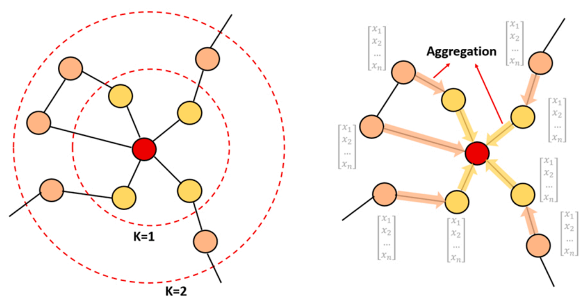

Fig. 5. Mechanism of graph neural network.

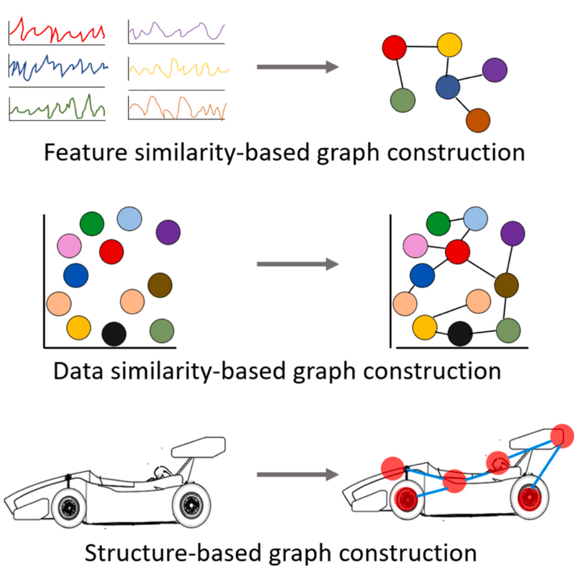

Fig. 6. Different graph construction methods of GNN.

a node. Straightforwardly, Euclidean distance can be adopted as a measurement of whether there is an edge between nodes [19]. Besides, the cosine similarity can also serve as a criterion to determine the relationship between two nodes [20,21].

Data similarity-based graph construction: it is difficult to apply feature similarity-based graph construction for univariate because it only has one feature. However, the univariate feature can be divided into subsamples and then act as nodes. Intuitively, the Euclidean distance between nodes can represent edge if their Euclidean distance is larger than a specific threshold [22]. In addition, connecting the adjacent nodes based on the k-nearest method and Gaussian kernel weight function are also effective pathways [23,24]. Following the similar logic, multivariate can also be divided into subsamples with the same time interval. Then graph can be established based on the similarity of subsamples, where each subsample has multi-dimensional features [25].

Structure-based graph construction: graph construction can also be based on equipment or manufacturing system. Khorasgani et al. [26] modeled manufacturing system in graph form where components served as nodes. Similarly, complex equipment can also be modeled in graph form. Chen et al. [27] established graph by structural analysis.

3.2. Knowledge graph

KG leverages a graphical structure to integrate and manage data, information and knowledge. It describes interconnected entities (e.g., objects, events, concepts) semantically. Fig. 7 shows KG construction process, where knowledge is extracted from multi-source data. The preliminary extracted knowledge is redundant and inaccurate, which needs to be integrated (knowledge fusion), and standardized by ontology schema. Furthermore, quality evaluation and knowledge complement processes refine KG. Semantic entities and edges enable KG to deduct feasible solutions for proactive queries and abnormal responses.

PdM-oriented KG has three types: Hierarchical KG, Property KG, and Hierarchical & Property KG, as shown in Fig. 8. Hierarchical KG hierarchically describes structure and causality, while Property KG represents different attributes parallelly. Integrated, Hierarchical & Property KG contains all the relationships as mentioned above.

Hierarchical KG: a KG organized components in a hierarchical manner, which provided an easily accessible way for troubleshooting [28]. In addition, KG represented hierarchical relationship among synergic mechanism, such as cause and effect [29].

Property KG: a Property KG uses to query basic information, latest maintenance log, corresponding status more quickly [30]. Meanwhile, a cloud computing technology was introduced to associate with dynamic environment to update Property KG timely [31].

Hierarchical & Property KG: to obtain a comprehensive solution, KG was designed to contain properties (such as duration, historical result) and hierarchical equipment relationship (such as 'is part of') [32].

3.3. Bayesian network

BN is a directed acyclic graph (DAG), where node denotes variables, and edge indicates a conditional dependent relationship (as shown in Fig. 9). Probability inference among variables is executed efficiently based on description of conditional dependence in BN.

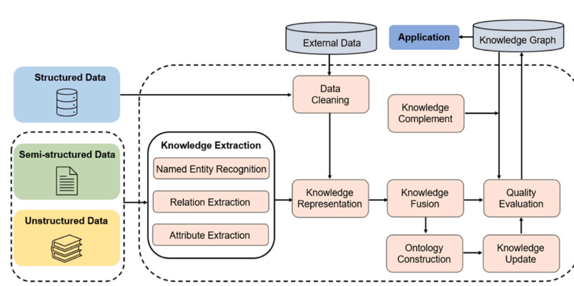

Fig. 7. The flowchart of KG construction.

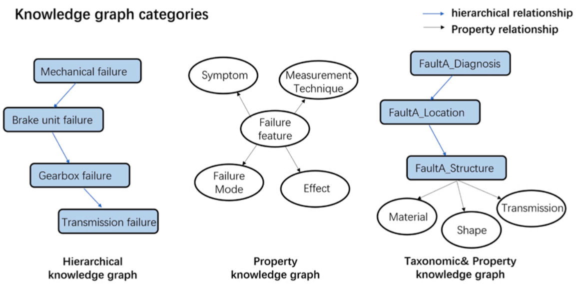

Fig. 8. Taxonomy of KG in PdM.

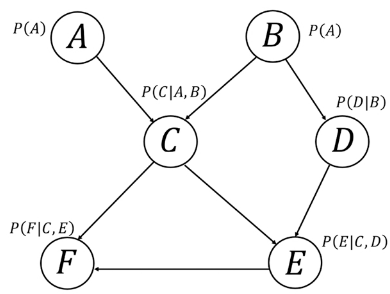

Fig. 9. A visual example of Bayesian network.

In terms of temporal scenario, a dynamic BN is introduced, where graph structure retains the same, but each node will be influenced by its value in last timestamp (Fig. 10).

3.4. Graph theoretic model

GTM is a generic term, indicating the deduction in graph structure with mathematical equations. In PdM, GTM can be classified as community detection, signed directed graph (SDG), graph feature generation, and label propagation (as shown in Fig. 11). It is noted that the node in GTM can be the features, samples, equipment components, events, stakeholders, etc. Compared with GTM, GNN narrows its scope to the first three items above.

Though the GNN and GTM have many same tasks, their core ideas are different. One significant difference is that GNN represents one of the deep learning approaches that iterate through the process of graph embedding, while the GTM deducts information, such as graph features and labels, based on the graph information. As a result, the GNN requires a relatively large amount of data to guarantee a robust graph embedding, while the GTM does not.

3.5. Comparison of different GbA

If a stakeholder has sufficient data in the manufacturing sector, it can

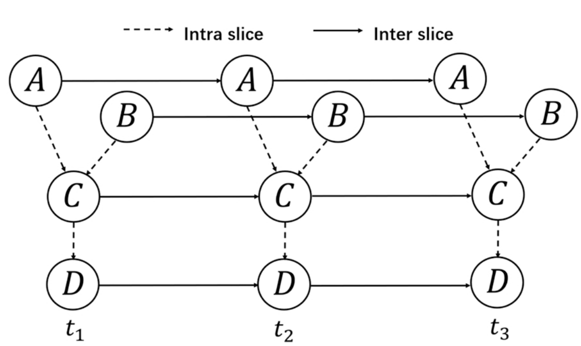

Fig. 10. A visual example of dynamic Bayesian network.

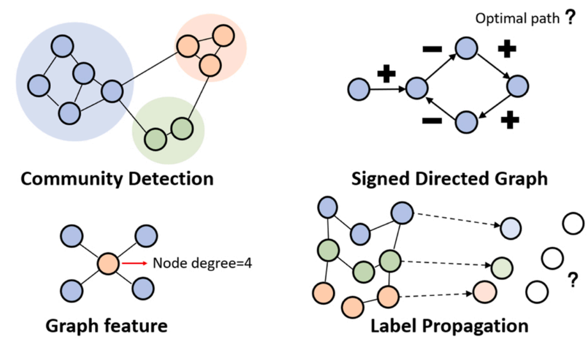

Fig. 11. Different Graph theoretic model.

use data-driven methodologies such as GNN and BN. One significant distinction is that the BN represents the dependent relationship, and its graph is directed, but the GNN's graph can be either directed or undirected. As a result, the BN demands the user to learn the sequential order of various nodes, while the graph of GNN may not need. Besides, the damage or failure correlation relationship and causal relationship are revealed by the BN's probabilistic graphical model.

In the meanwhile, the KG is appropriate for managing non-digital information, such as entities with semantic meaning. The KG organizes the knowledge in graph form for effective semantic reasoning. Hence, the KG can provide failure explanation and maintenance strategies recommendations based on its semantic meaning in the edges and entities.

Furthermore, GTM can be applied based on the graph structure alone, which is suitable for the situation of insufficient data. Besides, when the features are scarce, the GTM can provide new features to improve the data-driven models' performance or serve as maintenance criteria.

Overall, Fig. 12 summarizes different roles of GbA in monitoring, diagnosis, and prognosis steps according to their perception and cognition ability.

4. Application in predictive maintenance

In this section, the analysis follows the roadmap in PdM, including four main steps: anomaly detection, diagnosis, prognosis, and maintenance decision-making.

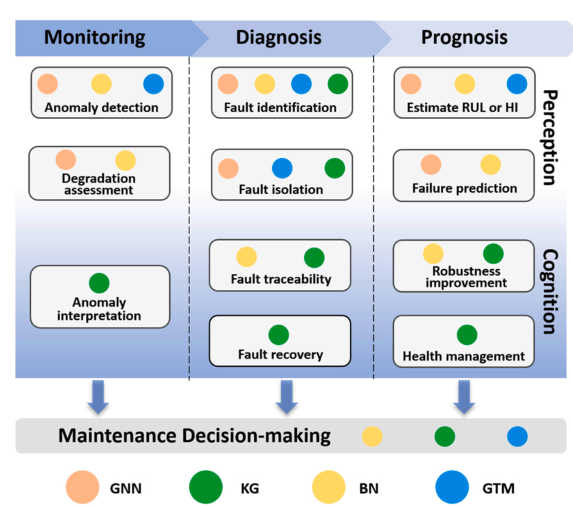

Fig. 12. GbA in monitoring, diagnosis, and prognosis.

4.1. Anomaly detection

Anomaly detection aims to inspect whether the manufacturing system is in a stable state or not. In the latter case, these detection methods should identify rare phenomenons in time and space. Limited data and label is the key issue in most anomaly detection tasks. Table 2 summarizes the categories of approaches in anomaly detection.

4.1.1. GNN for anomaly detection

Few-shot learning: semi-supervised Graph Convolutional Network (GCN) detects the anomaly by calculating the anomaly score with a dynamic threshold [33].

Feature engineering: GNN can generate significant features from original signal data to benefit downstream tasks. Wang et al. [34] proposed a graph-frequency spectrum method to search principal frequency features in temporal-spatial graph by leveraging unlabeled data. The anomaly will be detected if the principal frequency exceeds confidence interval in the Gaussian distribution.

4.1.2. KG for anomaly detection

KG can trace fault and simulate manufacturing processes based on stored maintenance information.

Searching: searching is a straightforward process. Different components' attributes are stored in KG, such as symptom and failure mode. Due to the anomalous change, abnormal components will be found in KG. Meanwhile, KG contained rules and lifetimes, which can be applied in searching process [36]. Giustozzi. et al. [32] introduced KG involving properties and hierarchical equipment relationship. Querying from this specific KG could detect the anomaly and conduct abnormal interpretation in a comprehensive manner.

Simulation: though the anomaly detection scenario lacks sufficient labels, external relevant knowledge can simulate manufacturing process for detection. Khan et al. [35] were inspired by the mechanism of immune system, providing a KG to manage knowledge of hierarchy and then simulate the virtual manufacturing process. The residual of virtual results and actual results can be served as fault tolerance score, indicating whether the fault occurs or not.

Table 2
Graph-based approaches for anomaly detection.

Categories	Pros and cons	Subcategories	Instance	Ref
Graph neural networks	Pros: the anomaly appears through aggregation. Cons: it is generally difficult to obtain effective graph embedding for heterogeneous graphs	GCN	Satellite telemetry	[33]
		Graph-based spectrum	Rotating bearing	[34]
Knowledge graph	Pros: detect the anomaly semantically. Cons: lack of incentive for the fresh anomaly type.	Hierarchical KG	Semiconductor	[35]
		Property KG	Aeronautic system	[36]
		Hierarchical & Property KG	Production line	[32]
Bayesian network	Pros: leverage limited knowledge Cons: limited data may lead to inaccurate probability.	BN	Chiller	[37]
		Dynamic BN	Factory management	[38]
Graph theoretic model	Pros: anomaly has significant graphical characteristics Cons: some anomaly features cannot be described in graph form.	Community detection	Semiconductor	[39]
		Graph feature inference	Aeronautic system	[40]
			Production line	[41]

4.1.3. BN for anomaly detection

BN calculates fault probability of abnormal observations. A classical BN calculates anomaly probability based on the pre-defined graph structure and the given variables [37]. Meanwhile, a dynamic BN associated with expert knowledge and temporal variables is proposed to infer anomaly events more accurately. In addition, erroneous cases can be used to adjust BN structure [38].

4.1.4. GTM for anomaly detection

Anomaly has distinguished features and special position in graph, which can be revealed by GTM.

Community detection: community detection aims to cluster nodes in different groups, where each set of nodes is densely connected internally. Wen et al. [40] integrated graph theory and Singular value decomposition (SVD) model to inspect health conditions, using singular values as nodes to construct the graph. The proposed graph-modeled singular values (GMSV) exploited interrelationship among singular values, and then achieved community detection.

Graph feature inference: graph feature inference generates significant features through propagation in graph structure. Lee et al. [39] constructed two graphs: measured-graph from historical log and prediction-graph from simulator. Then calculating the difference from the abovementioned two graphs, if their residual was higher than a certain threshold, it was confirmed as an anomaly. In addition, entropy of a thermodynamic system can be used to detect and isolate the fault. An attributed graph method was proposed to describe system's exergy flow based on residual technique and eigendecomposition technique [41]. This attributed graph provided structural features which contributed to anomaly detection.

4.1.5. Summary of different GbA for anomaly detection

One main characteristic of anomaly detection is the information scarcity, where GbA should combine with prior knowledge or special settings. Due to the lack of labels in anomaly detection, GNN in this sector can only conduct few-shot learning mechanisms or extract significant features. Besides, the GTM is targeted for unsupervised learning, which detects the anomaly via graph structure (community detection) or generates essential features. Meanwhile, KG, established by historical information and prior maintenance experience, can find anomalies through semantic searching. Similarly, the BN's graph should be built by combining the prior knowledge since anomaly detection scenarios often have insufficient information.

4.2. Diagnosis

Once anomaly is detected, it should diagnose whether it will evolve to damage or fault in the future. Diagnosis aims to determine whether there is a fault, and then identify the corresponding fault type and cause. Table 3 concludes different GbA in diagnosis.

4.2.1. GNN for diagnosis

GNN has been applied in fault diagnosis many times, which exploit synergistic relationship among data in graph form to detect the fault.

Fault diagnosis: GCN implemented convolution process in graph structure, which fully leveraged the similarity among features by various graph construction methods, such as Euclidean distance [22], Gaussian kernel weight function [23], K-nearest [52], singular value

Table 3
Graph-based approaches for diagnosis.

Categories	Pros and cons	Subcategories	Instance	Ref
Graph neural networks	Pros: explore the relationship among signal or equipment structure. Cons: the difficulty of precisely representing whole system or equipment in graph-level.	GCN	Power system	[22]
				[42]
			Electricity	[25]
			Water supply	[26]
				[19]
			Gearbox	[20]
				[21]
				[43]
				[44]
			Circuit	[27]
			Motor	[24]
				[45]
				[23]
			Rotating machinery	[46]
				[47]
				[48]
		Graph attention network	Rotating machinery	[49]
			Gearbox	[50]
		Discriminant graph	Rotating machinery	[51]
			Gearbox	[52]
			Chemical process	[53]
Knowledge graph	Pros: a KG can search feasible results with external knowledge and semantic graph structure. Cons: lack of numerical pattern recognition to support final decision	Hierarchical KG	Air source system	[28]
			Boiler	[54]
			Smart factory	[55]
			Microservice	[56]
			Elevator	[29]
		Property KG	Machine tool	[30]
			Bionic system	[31]
		Hierarchical & Property KG	Rotating bearing	[57]
			Spacecraft	[58]
			Loaders	[59]
			Car production	[60]
			Steam turbine	[61]
			Weapon Equipment	[62]
			Smart factory	[63]
			Semiconductor	[64]
			Machine tool	[65]
				[66]
Bayesian network	Pros: infer the failure type, matching up with semantic and logical understanding. Cons: difficult to recognize novel failure type.	DUCG	Nuclear power	[67]
				[68]
				[69]
		Traditional BN	Machine tool	[70]
			Rotating bearing	[71]
				[72]
			Air braking system	[73]
			Hot strip mill	[74]
			Diesel engine	[75]
			Machine tool	[76]
			Oil well drilling	[77]
Graph theoretic model	Pros: do not need data and plenty of external knowledge for recognizing the failure type. Cons: difficult to leverage data in a newly-develop scenario.	Community detection	Machinery	[78]
			Aero engine	[79]
		Graph feature inference	Gearbox	[80]
			Chemical process	[81]
			Nuclear power	[82]
			Rotating bearing	[83]
		SDG inference	Rotating bearing	[84]
			Spacecraft	[85]
			Radar	[86]
		Label propagation	Nuclear power	[87]

decomposition [43], equipment structure [27]. Meanwhile, a semi-supervised GCN leveraged a small number of labeled data for diagnosis [48,20,21]. Similarly, labeled and unlabeled data points were used to construct adaptive local graph to describe better the relationship among long-distance nodes by different edges' weights. With integrated objective functions, semi-supervised GCN can leverage unlabeled data to diagnose the fault [25]. Moreover, weight of different samples should be included to represent relation more precisely. A weighted horizontal visibility graph (WHVG) transferred temporal signal data into graph form, representing horizontal relationship between samples with their dynamic characteristics. In addition, edges' weights were slightly adjusted based on sample, weakening the influence from long-distance nodes [42]. Meanwhile, Yu et al. [44] introduced Fast GCN to diagnose the fault by reducing the number of nodes to accelerate training process.

Furthermore, various GCN-based approaches had been applied in diagnosis as well. Graph attention network applies weighting neighbor features with their dependent relationship. Facing multi-domain features, a triplet metric-driven multi-head GCN was proposed [50]. In addition, a conditional random field-based graph attention network in a semi-supervised mechanism was introduced [49]. It learned effective representation based on important nodes, which decreased the impact of limited data volume. Furthermore, there were more methods to connect the features based on their similarity. A SuperGraph is provided to describe the similarity of different features [45,46]. Each node in the SuperGraph was frequency feature-based subgraph, where same type of nodes are linked together.

Feature engineering: Yang et al. [52] embedded graph regularization into deep learning model to extracted discriminative features for fault diagnosis. Meanwhile, feature engineering can reduce feature dimensions to accelerate the training process. A discriminant graph embedding approach was proposed to extract significant features, which combined geometrical structure and label information [53]. Even worse case is the unlabeled scenario, which requires the proposed model to extract discriminative features. Zhao et al. [51] introduced a multiple-order graphical deep extreme learning machine (MGDELM) to balance graph structure of multi-domain features. Specifically, this approach preserved significance of different orders' features for unsupervised fault diagnosis.

4.2.2. KG for diagnosis

Unlike data-driven GNN, KG applies correlation analysis to diagnose the fault. In addition, KG can explain the causality of fault.

Searching: KG can conduct unrestricted [28] or restricted [29] searching for diagnosis. To apply diagnosis methods into a real manufacturing scenario, KG integrated with real-time heterogeneous industrial data in a standard way, and combined with Semantic Web Rule Language(SWRL) to detect the fault timely [64].

Currently, one primary challenge in real-time manufacturing process is integrating dynamic manufacturing data with static and well-structured KG. Wang et al. [55] established a rule library for mapping temporal signal patterns to specific rules for querying in KG. This mechanism was based on the assumption that dynamic temporal data can be mapped to node in KG. Similarly, Zhou et al. [57] introduced Hidden Markov Model (HMM) to recognize signal pattern, which served as querying elements in KG.

Furthermore, KG in manufacturing has been concerned more about human-centricity recently. In order to satisfy user-oriented requirement, a configurable fault diagnosis platform was introduced, where users configure their preference, such as confidence level of diagnosis result, type of causal inference, and monitor service [30]. Meanwhile, a universal KG for all stakeholders was proposed to maximize the utilization rate of knowledge during diagnosis [59]. Likewise, a human-computer interface was proposed to conduct condition monitoring and diagnostic analysis based on KG [58].

Reasoning: a multi-hop searching leveraged the combination of event, cause, and pattern for fault recognition and causal inference [63]. For further exploiting the relationship between symptom and fault, the SimRank algorithm calculated the correlation between symptom and fault, instead of semantic relation based on KG. This approach generated the coefficient of different factors and provided a confidence level for causal inference [66]. In addition, Wang et al. [60] introduced a KG-based qualitative mechanics theory to generate simulation results. Then the discrepancy between real data and virtual data can be used for diagnosis. Apart from fault identification, the analysis of root causes is also significant. Qiu et al. [56] constructed a KG to describe the hierarchical relationship of equipment by covering more areas and containing the operation factor. Therefore, a causal path was deducted by analyzing the weight and length of each path in this KG. Analogously, a diagnosis-oriented KG included fault cause layer, fault mode layer, and fault symptom layer, which can identify the faults and the corresponding root causes hierarchically [61].

Meanwhile, accompanied by the rise of artificial intelligence, a KG-based question and answer system was created for diagnosis, which improved the timeliness and interactivity of diagnosis processes in a semantic and readable manner [62]. In addition, Zhou et al. [65] leveraged manufacturing documents to establish the event evolutionary KG, and then develop a question and answer system. Unlike previous method, this KG conducted embedding-based reasoning with GNN approaches. Moreover, one challenge of applying KG in a real large-scale manufacturing system is how to accelerate reasoning time in KG. Xu et al. [31] introduced a bionic autonomic nervous system (BANS) with KG to allocate dynamic cloud resource in edge computing, which achieved automatic production in cloud server faster.

4.2.3. BN for diagnosis

BN conduct diagnosis and causal inference by its path.

Fault diagnosis: one prerequisite of BN is to define graph structure, Liu et al. [70] introduced the fault tree analysis to obtain the initial fault relation. Then BN leveraged the result of fault tree analysis as graph structure to diagnose the fault. Conditional probability in BN is represented in matrix form, which can be applied to probability inference. Zhang et al. [76] created a novel matrix product, named semi-tensor product (STP), which served as the core of probabilistic inference via matrix model, and then improved accuracy. In order to diagnose the fault in the limited data scenario, expert domain knowledge is required to associate with BN. Cai et al. [75] combined domain-specific rules with BN, where different situations linked to corresponding BN. This combination method was suitable for the scenarios that have limited numerical data, but plenty of domain knowledge. Meanwhile, systematical fault should be diagnosed in a standard way, Melani et al. [71] constructed BN by robust description of its systems and components from the systems modeling language (SysML) method. BN also faces the challenge of a dynamic environment, where external time and space changes weaken BN's reliability and accuracy. To fill the gap, Zhao et al. [67] established a dynamic uncertain causality graph (DUCG) to calculate the fault probability of temporal data firstly, and then transferred results into fuzzy decision tree for diagnosis. To guarantee the reliability and safety issues, event trees and fault trees were main methods to evaluate safety, which can be represented in DUCG form, respectively. Combining the result of the abovementioned two items to represent the probability is an effective way for diagnosis [68].

Causal inference: BN described the probability relation through edges, which relate to causal inference and correlate relation. Dong et al. [74] implemented correlation index (CI) to locate the fault, and then calculated the weighted average value to find causal path in BN. In addition, critical nodes in BN can be generated by quantitative measures and node reduction algorithms, where obtained nodes are used to represent significant elements in causality inference [72]. In addition, a Bayesian case-based reasoning system was proposed, which specialized in conducting causal inference for uncertain and complex environments [77]. Moreover, how to select features in BN will also influence its root cause analysis and diagnosis performance. Consequently, an unsupervised causality feature extraction method was proposed to simplify the attributes in BN, and tighten graph structure [73]. Furthermore, Dong et al. [69] proposed Cubic DUCG to update uninterruptedly in any time and space adaptively through negative sample iteration. This cubic DUCG deducted the overall causal path by traversing each adjacent time-slice causality path, which considered temporal issue for causal inference.

4.2.4. GTM for diagnosis

The fault can be diagnosed by its corresponding community, graph feature, SDG, and predicted label.

Community detection: similar to anomaly detection, the fault parts have a significant feature or particular position in graph. Sun et al. [78] applied composite graph with sparse subspace clustering (SSC) to cluster features for diagnosis, which eliminated nonzero elements in non-diagonal matrix. In addition, graph-based dimensionless similarity method was proposed to reduce diagnosis time but retain high accuracy level by decreasing embedding process of multi-dimensional features [79].

Graph feature inference: it is noticeable that graph form also improves diagnosis performance in numerous ways. Li et al. [81] provided a discriminative graph established from data points and their neighbor. This discriminative graph is combined with an Autoencoder model to extract significant features for fault diagnosis. Besides, graph can represent manufacturing process. Wang et al. [80] established graph by the similarity of signal data, and then diagnosed the fault based on state change.

SDG inference: to increase the timeliness and dependability, a SDG is a traditional method for inference. Qualitative trend analysis (QTA) is applied to determine parameters in SDG for diagnosis [87]. It is noticed that SDG form strongly influences diagnosis performance, where humans' subjective experience usually designs graph structure. To fill this gap, Chen et al. [85] combined data-driven method and expert experience to construct a more objective and precise SDG, which achieved real-time failure propagation and diagnosis. In addition, a complex system requires fault management hierarchically. Hence, SDG's edge should be regarded as the dependence relationship between components [86]. Meanwhile, SDG can utilize events as nodes to simulate manufacturing process, and conduct fault identification and causal reasoning through propagation. Liu et al. [82] integrated SDG with granular computing to simulate event occurrence, accelerating diagnosis speed but remaining a reliable accuracy. Moreover, attributes in SDG need a high-level representation if nodes involve many attributes. To obtain aggregated representation, SDG integrated with Intrinsic Time-scale Decomposition (ITD) to generate minimum Laplacian Energy (LE) index, which represented optimal rotational component as new node representation [83].

Label propagation: unlike GNN, label propagation only needs graph structure and limited label, without deep learning mechanism. Gao et al. [84] applied graph shift regularization to identify the fault by label propagation.

4.2.5. Summary of different GbA for diagnosis

Compared with anomaly detection, the diagnosis process has relatively sufficient data, which guarantees a promising performance of various GNN (such as Graph attention network, Fast GCN). Besides, the BN has sufficient data to provide persuasive probabilistic dependency relationships of fault causes. With the comprehensive KG constructed from sufficient data, some advanced algorithms can be applied effectively instead of semantic searching only. Finally, the GTM with label information can perform SDG inference or label propagation for fault diagnosis, in addition to unsupervised approaches (e.g., community detection and graph feature inference).

4.3. Prognosis

When the fault occurs, it leads to equipment degradation gradually. Prognosis is to predict remaining useful life (RUL), health indicator (HI), and degradation pattern to avoid production losses. This section analyzes the applications of GbA in prognosis, and the summarization is listed in Table 4.

4.3.1. GNN for prognosis

The proposed architecture of GNN is different from diagnosis because prognosis involves temporal information.

Failure prognosis: similar to applications of GCN in diagnosis, graph could be constructed by data or equipment structure for prognosis. Li et al. [88] built graph based on the correlation between extracted features (such as min, max, Kurt), where the extracted features serve as nodes. Then the proposed GCN is integrated with RNN to predict health conditions and degraded states. In addition, the Pearson Correlation Coefficients can be served as edges to construct graph. With well-constructed graph, RUL was estimated by GCN-RNN [89]. Apart from data-based graph construction, Man et al. [90] treated the measurement points as nodes, and their physical paths served as the corresponding edges to establish graph. Combining GCN and Gated Recurrent Units (GRU) as an integrated model, axle temperature can be predicted for prognosis.

Besides, GCN can be derived to different architectures for prognosis. A hierarchical attention GCN was proposed to fuse multi-modal signals for RUL, which considered the importance of different nodes [92]. Meanwhile, a CNN-GCN model was introduced, where the CNN conducted a convolution process for signal features to generate the features in high-order representation. Then the processed features fed into the Spatio-temporal GCN for aggregation to generate final prediction [93]. Furthermore, an approach attempted to model the equipment structure as a hypergraph form, where one edge is linked with more than two nodes. A novel framework applied hypergraph to represent the mechanical structure and adjust GCN into a hypergraph convolution neural network (HGCN) for prognosis [91].

4.3.2. KG for prognosis

Temporal data is difficult to leverage directly in KG, leading KG fail to predict the RUL or HI based on searching and reasoning. Therefore, KG aims to provide supporting information and causal inference in

Table 4
Graph-based approaches for prognosis.

Categories	Pros and cons	Subcategories	Instance	Ref
Graph neural networks	Same as diagnosis	GCN	Rotating bearing	[88]
			Aircraft engine	[89]
			Bogie	[90]
			Chemical process	[91]
		Hierarchical attention GCN	Aircraft engine	[92]
		GCN+CNN	Bearing	[93]
Knowledge graph	Pros: provide auxiliary explanations. Cons: cannot predict RUL or HI solely.	Hierarchical KG	Centrifugal pump	[94]
		Property KG	Rotating bearing	[95]
			Railway system	[96]
		Hierarchical & Property KG	Rotating equipment	[97]
			Machine tool	[98]
Bayesian network	Pros: represent time-dependent causal relationships Cons: lack of expansibility in large scale data.	Dynamic BN	Power system	[99]
			Nuclear power	[100]
Graph theoretic model	Pros: suitable for limited data. Cons: require temporal element.	Label propagation	Turbofan engine	[101]
		Graph feature inference	Hydro generator stator	[102]
			Rotating bearing	[103]

prognosis.

Searching: Liu et al. [96] used Xgboost model to calculate the importance factor, which acted edge's weight in KG. Then, querying from this KG can achieve supplementary information for prognosis. Meanwhile, with the rapid development of KG-based prognosis, numerous KG for different sub-domains in PdM are created, challenging for equipment or systems to use KG in cross-domain. A cross-domain KG was established to connect different KG semantically, overcoming the isolated KG problem. This cross-domain KG can find more preventive methods and prognosis more precisely [97].

Reasoning: prognosis domain has the abundant expert knowledge, which can be managed in KG for searching and reasoning. A typical KG, which involved the hierarchical structure of equipment and the properties of different components, was proposed to query and reason the potential failures and their causality in Prognostics Health Management (PHM) based on their symptom and the change of signal data [95]. In addition, a KG that recorded the patterns of monitoring data can estimate the health condition through active excitation modal analysis [98]. Meanwhile, one challenge is that prognosis rules and patterns in KG do not have same criteria. A standard ontological model, OntoProg, was introduced to align various prognosis rules universally with international procedure standards. With such improvement, prognosis and causal inference can be more accurate due to the greater knowledge coverage [94].

4.3.3. BN for prognosis

Prognosis relates to temporal information, hence the dynamic BN is tailored for this scenario.

Failure prognosis: a dynamic BN was proposed to prognose the failure for a complex system or equipment, which involves dynamic interaction information. This dynamic BN included operator behavior, environment information, component health, and system health, so as to monitor health state continuously [100].

Causal inference: the probability in BN can represent the degradation probability in prognosis. In order to model the structure of complex system in BN form, an approach combined fault tree analysis (FTA) and dynamic BN to manage the interdependent and hierarchical relationship of various features. With the pre-trained dynamic BN model, a new input case can obtain its RUL or HI, and its corresponding causal path [99].

4.3.4. GTM for prognosis

The time-series graph can describe temporal factors to deduct the degradation pattern. Besides, graph feature extraction also improves prognosis performance.

Label propagation: a complex system has more than one degradation simultaneously, which may lead to different and confusing results. How to integrate these different degradation patterns become an essential issue in prognosis. Xu et al. [101] introduced time series chain graph (TSCG) to model the dependencies between degraded factors. Based on the obtained temporal dependency relationship, the measurement of different degradation conditions can be used to conduct a system-level prognosis.

Graph feature inference: similar to diagnosis applications, GTM can model equipment structure in graph form. A Physics-of-Failure (POF) prognostic model simulated the failure propagation based on the equipment's physical structure, and then estimated whether it followed a health distribution or not [102]. Moreover, focusing on feature extraction, a graph spectrum reconstruction approach was proposed to generate more discriminative features to improve the performance of HI prognosis [103].

4.3.5. Summary of different GbA for prognosis

Because RUL and HI decrease over time, the data-driven prognosis model should involve the temporal elements. Therefore, the data-driven GbA should be used in conjunction with the time series model for prognosis. For instance, the temporal GNN model, the dynamic BN, and TSCG (temporal GTM). Meanwhile, the current KG does not specialize in combining the degraded signal process, but its ability of correlation analysis and causal inference benefits the health management in prognosis.

4.4. Maintenance decision-making

After diagnosis and prognosis, the equipment or the manufacturing system should conduct corresponding solutions to prevent or mitigate the fault. Table 5 indicates different GbA in maintenance decision-making.

Table 5
Graph-based approaches for maintenance decision-making.

Categories	Pros and cons	Subcategories	Instance	Ref
Knowledge graph	Pros:provide integrated result Cons: difficult to synchronize with external knowledge	Hierarchical & Property KG	Aircraft	[104]
				[105]
			Power system	[106]
			Shield tunelling	[107]
Bayesian network	Pros: conduct strategies with failure probability Cons: difficult to construct the graph	Traditional BN	Natural gas	[108]
Graph theoretic model	Pros: simulate manufacturing process Cons: fail to provide diverse decision	Graph feature inference	Supply chain	[109]

It is noted that GNN has not been applied to maintenance decision-making so far. This is because when used for predictive maintenance, GNN's graph consists of features, samples, and equipment components. Therefore, the outcome of the GNN indicates which part is significant or provides an overall prediction of diagnosis and prognosis results, while it does not output specific maintenance strategies.

In other domains, however, GNN has collaborated with various methods to generate strategies and solutions. For example, GNN combines reinforcement learning with reason feasible strategies in manufacturing scheduling. It is hoped that GNN can be used in maintenance decision-making in the future [110].

4.4.1. KG for maintenance decision-making

KG provides valuable information and recommends feasible solutions for maintenance decision-making.

Searching: KG provides relevant information for further maintenance, such as type, past useful life, which offers essential decision-making information. The visualization of KG enables users to understand causality by graph path [105]. Furthermore, a KG can provide a collaborative working condition for multi engineers to query and communicate in same context but different places. This KG lets the engineers maintain the equipment or system in a reliable and comprehensible manner, fulfilling goal of the user-centricity paradigm [107].

Recommendation: KG can serve as a configuration generator tool by recording maintenance reports and the overall best configuration in KG [106]. Toward the human-friendly self-awareness manufacturing system, a cognitive maintenance system is proposed to create contextual recommendations involving time, location, budget, and boundary. The detected patterns and failure symptoms are served as the input elements for fuzzy querying in KG. The contextualized results will be delivered to the engineers or operators for maintenance tasks. After the maintenance tasks, engineers or operators update KG based on the tasks' performance [104].

4.4.2. BN for maintenance decision-making

Apart from treating features as nodes, BN's nodes could represent different events or factors in manufacturing for maintenance decision-making. Leoni et al. [108] calculated the maintenance interval as recommendations to optimize the maintenance scheduling based on BN, where the corresponding graph contains failure modes and equipment components. It should be highlighted that when features can represent events or factors, a BN can be formed in this way.

4.4.3. GTM for maintenance decision-making

GTM simulated different situations for maintenance scheduling. A game theory was carried out to maximize suppliers' revenue by considering the production and maintenance costs in corresponding pricing strategies. The proposed leader-multiple-followers game sets the supplier as leaders, and the customers as followers, achieving the best joint optimization price strategy in maintenance solution [109].

4.4.4. Summary of different GbA for maintenance decision-making

Maintenance decision-making aims to provide practical configurations, instructions, strategies, etc. Therefore, the GbA should incorporate the elements listed above in their graph. KG is a viable platform to include these factors semantically. Besides, the graph of BN and GTM can represent other kinds of relationships to undertake decision-making, such as events relationships, instead of traditional feature relationships. Furthermore, GNN could integrate with other methods to offer feasible maintenance solutions, although current research has yet to attempt such a combination.

5. Challenges

5.1. Noise and error of manufacturing data

Manufacturing data is collected from various channels, including sensor devices, manual logbooks, visual images, etc. While multi-tasks are conducted simultaneously in the manufacturing scenarios, their symptom and performance will be recorded in the same device at the same time inescapably. Theoretically, one particular feature only contains data of the corresponding meaning. However, most cases do not satisfy this requirement, because data collection takes place in a compact environment, other irrelevant tiny fluctuations will be measured. Therefore, the collected data involves irrelevant information, leading to poor model accuracy.

5.2. Limited labeled data

Increasing manufacturing systems have installed sensor devices in their related equipment under the smart manufacturing paradigm. With the Internet of things devices and standard logging, collected data has large enough. In comparison, the generation of failure labels needs the exhaustion of equipment's life cycle, which takes a long time and causes substantial economic losses. Therefore, the labeled data is limited and valuable in the manufacturing domain.

Apart from insufficient training due to limited labeled data, GbA still meets extra difficulty. In GNN applications, most labels are graph-level rather than node-level or edge-level, restricting the feasibility of relevant tasks (such as node classification). Besides, KG contains various entities, while the limited label results in fewer entities of fault type. Under this circumstance, the distribution of entities' types becomes a long-tail distribution, where the tail is related to the failure-based entities. As a result, maintenance-based searching and reasoning processes become time-consuming and inefficient in locating the failure-type entities.

5.3. Hierarchical diagnosis and prognosis

The complex equipment or system has a hierarchical structure, leading to different kinds of failure and corresponding maintenance strategies. After recognizing failure patterns or estimating remaining useful life, it is significant to determine its systematical damage level and fluctuation. Graph provides an effective platform for managing hierarchical knowledge, but there is a long way to achieve hierarchical PdM. Firstly, current diagnosis research concentrate on fault identification, while fault components tend to cause the abrasion of adjacent components. Fault identification cannot provide a complete perspective for further maintenance decision-making without detecting affected area. Similarly, previous researchers treated prognosis as a regression problem but failed to recognize its variation pattern, RUL and HI of other adjacent components. Though previous approaches have obtained remarkable results, they focused on one particular component rather than consider the associated potential risk components, failing to estimate the hierarchical damage situation. Secondly, most GbA constructed graph based on data similarity, but few graphs are based on the equipment structure. The equipment structure-based graph can describe the relationship among different components hierarchically. Based on the structure, if one specific node has failure symptoms, its first-order nodes and other associated nodes will have potential failure risk. Furthermore, if graph has diverse edge types and weights, GNN can detect more potential damage nodes. However, most previous works neglect to model equipment or system structure in graph form.

5.4. Incorporation with incremental data

Manufacturing system is dynamic, where collected data increases with time. Data-driven approaches (e.g., GNN and BN) split available dataset into training data and testing data, and validate the performance and generalization by feeding the testing data into trained model. Training data used by many data-driven models typically come from datasets with the same distribution, although data encountered in real-world applications may have different distributions. This is because data acquired in a production environment may be non-stationary since the conditions of the machines and environment may be time-varying. Therefore, these trained models may decrease their efficacy if placing them online. Furthermore, one challenge of KG is how to update facing a dynamic environment. Currently, KG does not involve update mechanisms in the PdM domain, which may fail to provide time-efficient maintenance solutions.

5.5. Verification mechanism of graph structure

Graph structure is established by expert experience, sample-based or feature-based similarity calculation, equipment structure, etc. At the same time, most established methods are based on the collected data or prior knowledge, which does not guarantee their correctness. Therefore, a verification mechanism for the proposed graph is a safeguard for the approaches' performance. Nevertheless, most GbA applications do not have a graph structure examination. Under this circumstance, if graph contains redundant and error information, perception and cognition will spend more time. Even worse, the inaccurate graph structure causes invalid propagation and aggregation, resulting in wrong prediction.

6. Future and opportunities

6.1. GbA-based hybrid mode in PdM

One of the mainstream approaches in PdM is model-based approach, which concentrates on simulating industrial processes or equipment structures. Meanwhile, implicit equipment and system's mechanisms provide insightful causal inference knowledge. Based on the systems or equipment, the model-based approaches compare the difference between simulated output and measured output and narrow down the gap as much as possible.

On the other hand, PdM's data-driven approaches have become increasingly popular with the rise of deep learning. Apart from current hybrid modes in PdM [111], the appearance of GNN provides a new opportunity for the integration of model-based and data-driven-based approaches. Though most GNN approaches establish graph through data similarity, some works construct graph following the principle of model-based approaches. Model-based approaches provide interpretable knowledge of equipment structure, improving the comprehensiveness of cognition. Meanwhile, BN is also expected to serve as a bridge for hybrid mode in PdM since it is a graph-based data-driven approach. Furthermore, recent works have applied KG to represent and cognize the equipment mechanism in an event graph [112], which is expected to cooperate with data-driven models for cognitive PdM in the future.

6.2. Self-X cognitive PdM

A more progressive vision of cognitive PdM is that the manufacturing system detects, diagnoses, prognoses, and maintains automatically and intelligently. KG can search for potential failure and recommend relevant solutions based on GNN. Current research has found required nodes as outputs, while it is difficult for users to understand their implicit meaning. The users have to rethink the corresponding recommendations or solutions by referring to domain knowledge and current situation, which is time-consuming and unfriendly to fresh engineers.

KG is a feasible tool to achieve Self-X capabilities, including self-configuration, self-optimization, and self-adaptiveness [113]. Specifically, (1) self-configuration means automation of on-demand manufacturing is achieved by applying the standard software and hardware interfaces to configure manufacturing resources [114]; (2) Self-optimization indicates the achievement of the best manufacturing performance based on reorganizing manufacturing resources [115]; and (3) self-adaptiveness aims to identify any variations and anomaly in manufacturing process, then deal with potential breakdown autonomously [116].

The Self-X paradigm provides an end-to-end solution in PdM, with accurate recommendations and automatic configurations. GNN is practical approach that facilitate the self-X ability, which conducts embedding-based reasoning. The reasoning processes include link prediction, node classification, disambiguation, etc. The Self-X paradigm provides a new perspective that the final output of KG's reasoning should be the complete solutions rather than the entities only. Furthermore, increasing attention had been put into multi-level maintenance in manufacturing system, involving the benefit of different stakeholders [117], and the production scheduling [118,119,120]. KG enables to determine causality and provides automatic restoration, adjustment, and optimization, promoting the cognitive ability of smart manufacturing systems.

6.3. Continuously evolvement of graph structure

Online PdM system should invoke GbA continuously, ensuring the operation without interruption. However, most graphs in GbA are constructed by historical data and domain knowledge, which may reduce its effectiveness and cognition in the future. Furthermore, causal inference relies on the accuracy of graph structure. Therefore, the continuous evolvement of graph structure becomes a significant topic. Dynamic KG complement has recently become a popular topic because it provides the connections for new entities [121]. Furthermore, researchers have put more attention on dynamic graph (such as dynamic GCN [122]). However, these approaches have to be based on plenty of temporal data and corresponding labels, which is difficult to achieve in manufacturing scenarios. Solving the evolution of graph will become the critical issue of the applications of GbA toward cognitive PdM on a large scale.

6.4. Collaborative PdM

Limited data and labels are one of PdM's challenges, which restricts the broad applications of Data-driven models. Knowledge-based approaches provide a feasible solution for insufficient data situations. However, the different PdM tasks have different boundness, creating information silos. Fresh engineers or start-up industrial systems fail to accumulate enough failure experience, leading to a higher probability of breakdown in initial stage. However, those experiences can be learned from different stakeholders. Therefore, different stakeholders should have the equal sharing mechanisms to break down the information barriers.

A straightforward idea is to share their maintenance knowledge and fault pattern. However, one concern is the privacy and security of data. Data privacy has excellent profit in manufacturing regarding potential conflict and commercial factors [123,124]. Blockchain provides a distributed database as an immutable ledger that allows digital information to be recorded and distributed but not edited. Currently, blockchain had implemented in numerous disciplines, including manufacturing domain [125]. In addition, some stakeholders do not want to publicize their historical knowledge even though they have the right and ownership. Under this circumstance, federated learning provides a platform to train a data-driven model based on multiple decentralized edge devices or servers, which store local private data samples without exchanging their data [126]. Federated learning guarantees that each participant will not expose its private data but achieve better collaboration performance. This federated learning mechanism can benefit data-driven models and KG construction in PdM.

7. Conclusions

GbA, including GNN, KG, BN, and GTM, use graph to connect among different events, components, parts, data points, features, etc. Nevertheless, many GbA in PdM research concentrate on algorithms' performance, but few relate to correlation analysis and causal inference. GbA can build the connection among the relevant failure components and events, achieving the cognitive PdM by fault causal inference, associated components inspection, hierarchical maintenance, etc. In order to summarize different usage of various GbA in the cognitive intelligence framework, identify their limitations, and forecast the future direction, this paper conducted a systematic literature review of 91 academic articles on GbA in PdM. The main contributions of this study can be highlighted below:

Outlined the typical graph construction methods in PdM. Because the signal features and equipment do not own graph structure initially, this paper concluded three ways to establish graph in GNN: data similarity, feature similarity, and structure-based modeling. Meanwhile, KG construction can be divided into Hierarchical KG, Property KG, and Hierarchical & Property KG. Moreover, the graph construction methods of BN and GTM are also summarized.

Holistically reviewed the GbA to achieve cognitive PdM. Cognitive intelligence plays an increasingly important role in PdM, and GbA is an effective method to achieve it. Toward the cognitive intelligence, selected publications were analyzed their perception, cognition (correlate analysis and causal inference) in each PdM's step.

Highlighted the challenges and future perspectives of GbA in PdM. After the comprehensive review, five main challenges of GbA were proposed, containing low data quality, adaptive for dynamic graph, incomplete maintenance. Meanwhile, this paper raised four future perspectives towards the cognitive PdM and the practicability of GbA.

It is hoped that this research can provide a fundamental basis for researchers and industrial practitioners in adopting GbA-based PdM and initiate several future research directions to achieve the cognitive PdM.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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