35th European Modeling & Simulation Symposium
20th International Multidisciplinary Modeling & Simulation Multiconference

2724-0029 © 2023 The Authors.
doi: 10.46354/i3m.2023.emss.012

A Knowledge Graph Reasoning Framework for Manufacturing Multi-view Heterogeneous Data

Jinyun Cai[1], Lei Ren[1,2,3,*], Weilin Qin[4], Lin Zhang[1] and Liyuanjun Lai[1]

[1]School of Automation Science and Electrical Engineering, Beihang University, 37 Xueyuan Road, Haidian District, Beijing, 100191, China
[2]Zhongguancun Laboratory, Beijing, 100094, China
[3]State Key Laboratory of Intelligent Manufacturing System Technology, Beijing, 100854, China
[4]Beijing Aerospace Smart Manufacturing Technology Development Co., Ltd, 49 Badachu Road, Shijingshan District, Beijing, 100144, China

[*]Corresponding author. Email address: renlei@buaa.edu.cn

Abstract
Multi-view heterogeneous data in the manufacturing industry contains a wealth of information, and comprehensive analysis is needed to discover potential regularities and relationships, thus becoming a key issue in the development of intelligent manufacturing. Data quality and consistency in manufacturing knowledge graph reasoning systems are facing severe challenges. This paper proposes a knowledge graph reasoning framework, which constructs a knowledge graph based on manufacturing multi-view data for deep data mining and intelligent decision support. The knowledge graph construction framework is established through a four-layer structure. The paper presents a manufacturing multi-view data management framework, and designs a modeling and processing mechanism of multi-view data. The proposed framework presents a systematic solution for managing and analyzing manufacturing data, and provides an important theoretical framework for establishing an intelligent governance model of manufacturing data.

Keywords: Knowledge graph; knowledge reasoning; multi-view; manufacturing big data; intelligent manufacturing

1. Introduction

With the advancement of the manufacturing industry and technological progress, the amount of data generated by enterprises in the production process has increased dramatically. The data includes production data, equipment data, quality data, etc. which are potentially valuable resources, but also pose great challenges to data storage and analysis. The manufacturing industry is undergoing a digital transformation, and enterprises need to use advanced data analysis technology to improve production efficiency, reduce costs, and optimize supply chains. Data architecture is the basic source for communication, decisions and processes (Krumay and Rueckel, 2020). Manufacturing big data is regarded as a means of production to drive intelligent manufacturing (Wang et al., 2022).

The emerging information and communication technologies, exemplified by cloud technology, artificial intelligence, big data, digital twin, and 5G connectivity, are driving the global industrial manufacturing industry towards digitization, networking, and intelligence (Ren et al., 2021). Data-driven industrial intelligence keeps emerging, such as predictive models, digital twins and intelligent factories (Ren et al., 2020). Intelligent manufacturing systems are now capable of performing tasks such as online identification, monitoring, and prediction derived from production data, assisting people in analyzing the manufacturing process (Tao et al., 2022; Greasley, 2022).

Multi-view heterogeneous data in the manufacturing industry refers to the diverse data collected from different perspectives and data sources, which are used to describe and analyze information on the manufacturing process, product quality, equipment status, supply chain, etc. By collecting multi-view data, information from multiple angles and levels can be obtained to have a more comprehensive understanding of each link, equipment status and quality in the manufacturing process. Through comprehensive analysis of multi-view data, potential problems, improvement opportunities and optimization potentials can be discovered. On this basis, the analysis and reasoning of multi-view data can diminish the uncertainties in decision-making and the dependence on subjective judgment, thus improving the accuracy and reliability of decision-making. For manufacturing enterprises, intelligent governance of manufacturing data has the following benefits: improving decision-making efficiency, optimizing production processes, reducing costs and enhancing competitiveness. Enterprises can obtain valuable information faster and provide management with a reliable basis for decision-making. And it is easier for enterprises to identify potential problems in the production process so that they can take corresponding measures to improve production efficiency and product quality. In addition, enterprises can better predict and control costs to achieve a reasonable allocation of resources. Finally, enterprises can better understand market demand and competitive situation, so as to develop targeted marketing strategies and improve competitiveness.

Knowledge graph technology plays a crucial role in big data analysis, which can screen and analyze massive fragmented information data in time, and finally summarize and sort out the required information, including data visual analysis, data mining, semantic engine construction, knowledge reasoning, etc. Knowledge graph-driven technology can quickly provide a visual interface for constructing, retrieving, and analyzing data resource knowledge bases. The essence of knowledge graph is a knowledge repository based on the concept of the semantic web, wherein entities are represented by nodes in a directed graph, and edges of the directed graph are used to represent the various semantic relationships between the entities. Therefore, the graph structure can be used to identify, model and reason the complex association between things and precipitate domain knowledge, so that the machine can understand the knowledge and carry out corresponding reasoning calculations on this basis (Qi et al, 2017; Wang et al, 2020). The combination of knowledge graph and manufacturing big data greatly promotes the development of intelligent manufacturing.

At present, the challenges encountered by knowledge graph technology in the intelligent manufacturing field include the following two aspects. Firstly, single-view data only provide information from a specific angle or dimension and cannot cover all aspects of objects, nor provide enough information to explain complex associations and causal relationships. Secondly, there are problems such as data incompleteness, data inconsistency, and data defects in the manufacturing knowledge graph. Fully mining and utilizing the implicit knowledge contained in the structural data of the manufacturing knowledge graph can be challenging.

In light of the previously mentioned two problems, the paper proposes a knowledge graph reasoning framework for manufacturing multi-view heterogeneous data, designed to solve the issues faced by manufacturing knowledge graph in data analysis and management as well as decision support. This paper is structured as follows: section 2 introduces the related work of manufacturing knowledge graph. Section 3 presents the knowledge graph reasoning framework. Section 4 summarizes the conclusions and future work.

2. Related work

2.1. Manufacturing Knowledge

Manufacturing knowledge refers to all kinds of knowledge and information related to manufacturing. It covers all aspects of the manufacturing process, including production processes, equipment and tools, materials, quality control, supply chain management, product design, product development, etc. The core purpose of manufacturing knowledge is to increase production efficiency, reduce costs, optimize product quality, and meet changing market demands. The exponential increase in industrial data gathered from a variety of manufacturing processes holds significant information and potential value related to industrial products (Ren et al., 2021; Ren et al., 2022). For example, (He and Jiang, 2019) calculated both relational term similarity and intrinsic term similarity between a pair of manufacturing knowledge entities. (Hannola et al., 2018) put forth a conceptual framework, which aims at enhancing industrial production workers through digitally enabled knowledge management processes, resulting in benefits for workers as well as increased job efficiency and productivity. (Liu et al., 2022) put forth a digital twin process model (DTPM) construction method, on the basis of the processing characteristics of knowledge evolution. This approach addresses three crucial technologies: the connectivity framework of process knowledge, the representation technique of evolutionary geometric characteristics, and the connection strategy between them. (Meski et al., 2020) introduced an approach to global knowledge management, involving the examination and creation of a structured model for the knowledge repository, followed by the deployment of tools in knowledge engineering. (Kim et al., 2017) suggested a method for calibrating local models, which incorporates the domain expertise into engineering process models using local model averaging technology. (Zhang et al., 2020) proposed a methodology for enhancing analytical models with domain knowledge to address issues related to interoperability and traceability within pertinent domain knowledge employed in the development of analytical models. (Li et al., 2022) put forward TDKIPP to carry out knowledge-driven intelligent process planning for aerospace components. (Zheng et at., 2021) proposed a multi-level heterogeneous model data framework, which aims to solve the challenges encountered by the digital twin system of intelligent factories in managing virtual models.

2.2. Multi-view learning

Multi-view means that the same thing can be described from different angles. Splicing the feature vectors corresponding to different views can form a unified high-dimensional single-view data, but there are disadvantages such as easy overfitting and noise introduction. In addition, multi-view data often has practical problems such as high dimensionality, heterogeneity, missing views, and an insufficient number of training samples, which increase the difficulty of multi-view learning. (Zhang et al., 2016) put forth a multi-view collaborative learning approach to maximize the correlation between different views in the kernel space and alleviate the problem of feature dimension imbalance of different views. (Zhang et al., 2018) introduced a multi-view clustering approach derived from self-expressive subspaces, which showed significant advantages in high-dimensional data clustering. (Zhang et al., 2017) put forth a hierarchical multimodal metric learning method aiming at multimodal classification, decomposing the metric corresponding into two parts related to modality and modality sharing. The multi-view graph embedding framework (MGAT) proposed by (Xie et al., 2020) is aiming at multi-view networks to learn global node representations. MGAT considers different attributes of each view and the rich information in different views directs processing between nodes, so it is able to effectively encode multi-view networks.

2.3. Manufacturing Knowledge Graph

A knowledge graph-based knowledge database in the intelligent manufacturing field can be used to express the characteristics of both data and knowledge, and the inherent connections between data and knowledge. (Ren et al., 2022) introduced a manufacturing knowledge graph construction framework (FMKG), aiming at integrating intricate knowledge to construct a domain knowledge graph. In addition, they proposed a graph embedding model based on attention (ABGE) for discovering the complex relationship between nodes, so as to complete manufacturing knowledge graph. (Li et al., 2019) applied knowledge graph to industrial software code generation and develop a knowledge inquiry system equipped with capabilities like parameter search, variable computation, code calling, and ontology reasoning. In the case, the route planning of industrial AGV was realized and the corresponding code was generated. (Zhou., 2021) suggested a production resource allocation method driven by knowledge graph, which can output the equipment set required for a specific task according to equipment information and order information, and make rapid resource allocation decisions for the insertion task.

In order to fully mine and utilize the tacit knowledge contained in manufacturing knowledge graph, knowledge reasoning technology in intelligent manufacturing is gradually developed. Knowledge graph reasoning includes entity prediction, link prediction and knowledge graph completion, aiming to infer new knowledge and identify wrong knowledge on the basis of established knowledge. (Vashishth et al., 2019) put forth the CompGCN model, which takes into account the aggregation of relational features and the heterogeneity of knowledge graph, jointly learns the vector representation of entities and relations, and defines the feature aggregation function. (LI et al., 2021) put forth a graph neural network model based on a heterogeneous information network (HRAN), which aggregates the features of adjacent nodes step by step through entity and relational levels, and aggregates different types of semantic feature information based on relational paths.

3. Knowledge Graph Reasoning Framework

A knowledge graph reasoning framework for manufacturing multi-view heterogeneous data is proposed. This framework consists of four layers: manufacturing data acquisition layer, manufacturing data management layer, manufacturing knowledge reasoning layer, and application layer, as shown in Figure 1.

3.1. Manufacturing Data Acquisition Layer

The first layer of the framework is the manufacturing data acquisition layer, which is aimed at acquiring manufacturing multi-view heterogeneous data. This type of data include data with heterogeneous characteristics acquired from multiple data sources and different perspectives and dimensions in the field of manufacturing. These data include information from sensors, equipment, production lines, quality control, supply chain, etc., covering all links and key indicators in the manufacturing process. Each view provides a specific aspect of data description, including different attributes, characteristics and indicators, and the data have differences in structure, format, type and source, thus requiring data integration and processing. Moreover, these data reflect the differences and associations among different data sources and perspectives in the manufacturing industry. In order to reveal potential associations, regularities, and insights, integration, association, and analysis are required, so as to provide a valuable information basis for production optimization, quality improvement and decision-making in the manufacturing industry.

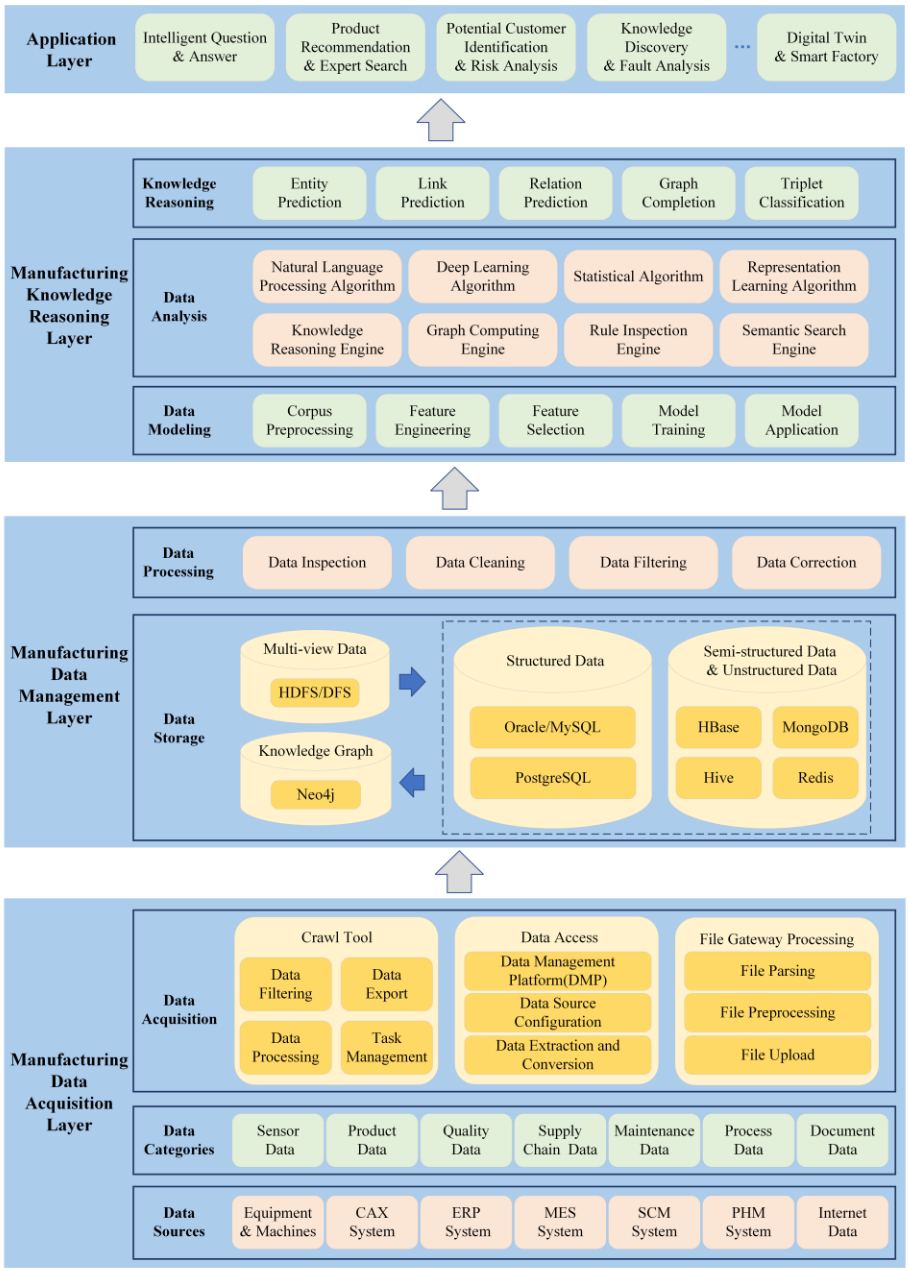

Figure 1. Knowledge graph reasoning framework for manufacturing multi-view heterogeneous data.

Manufacturing multi-view heterogeneous data can be acquired from various sources, mainly including the following aspects:

- Manufacturing equipment and machines. Modern manufacturing equipment and machines are commonly equipped with sensors and data recording devices, which can generate vast quantities of real-time data, such as machine status, operating efficiency, fault records, etc.
- Computer-aided Technology (CAX) system. The CAX system includes multiple subsystems such as computer-aided design (CAD) which provides product design and modification data, computer-aided manufacturing (CAM) which provides product manufacturing process data, and computer-aided engineering (CAE) which provides product testing and simulation data.
- Enterprise Resource Planning (ERP) system. Serving as a type of enterprise information

management system, the ERP system can provide data on orders, logistics, production, quality, cost, etc.

- Manufacturing Execution (MES) System. The MES system manages and controls the real-time execution of the manufacturing procedure, offering data on process parameters, equipment status, production plans, etc.
- Supply chain management (SCM) system. The SCM system can provide data on material supply, product demand, inventory status, etc.
- Predictive Health Management (PHM) system. The PHM system can provide data on equipment health, failure predictions, maintenance recommendations, etc.
- Internet data. Manufacturing-related professional forums, online websites, social media, news reports, etc. can also provide valuable manufacturing data.

For modern manufacturing equipment and systems, there are usually corresponding interfaces or APIs that can be used for data acquisition. For CAX, ERP, MES, SCM and PHM systems, data can be acquired by accessing their background databases. For Internet data, web crawlers can be used to capture and collect data. And the data mainly include the following categories:

- Sensor data. Sensors and equipment in the manufacturing process can collect various data, such as temperature, pressure, vibration, current, etc. to monitor equipment status and changes in the production process.
- Production data. Equipment and machines on the production line can record data such as production speed, product count, yield rate, defective product information, etc. to monitor production efficiency and quality.
- Quality data. Product quality data such as size, weight, and appearance defects are recorded for quality control and improvement.
- Supply chain data. Data related to suppliers, logistics, inventory including supplier information, transportation time, inventory levels, etc. are used to optimize supply chain management and material procurement.
- Fault maintenance data. The data include equipment maintenance records, fault reports and maintenance logs, etc. to provide information on equipment failure, maintenance time and maintenance history.
- Process data. The data include the process schemes and methods used in the production process to control, which adjust the production process to obtain the required product quality and performance.
- Document data. The data include design specifications, process flow, technical documents, etc. to provide information on product design, process guidance and specification requirements.

The specific data acquisition methods are divided into three types, including crawler tools, data access and file gateway. Firstly, for Internet data, an acquisition solution combining commercial crawler tools and customized development can be used. Specifically, commercial crawling tools can be used for normalized web pages. For websites that are difficult to obtain, such as news websites, websites that collect data from multiple websites, and websites with different access rules, custom-developed crawlers can be considered. The process of using crawler tools to collect data includes data filtering, data processing, data export, and task management. Secondly, the DMP system can be used in data access to realize data source configuration and data extraction and conversion. The data access method involves different types of data sources. After development and configuration, each template is formed and aggregated into a dynamic configurable template library. When the data access task is issued, it can be matched from the configurable template library. Thirdly, the file gateway processing method is to collect files and data from different sources, preprocess them according to certain rules, and store them uniformly in the big data platform. It mainly includes three functions: file parsing, file preprocessing and file uploading.

3.2. Manufacturing Data Management Layer

Manufacturing multi-view heterogeneous data can be acquired through the data acquisition layer. The second layer of the framework is the data management layer, which is mainly responsible for processing and storing the collected data, and then providing high-quality and easy-to-use data support for knowledge reasoning and application. Data from different sources may contain noise, redundancies, errors and inconsistencies. Data cleaning and preprocessing can improve data quality, making data more accurate, complete, consistent and usable. In addition, the acquired data are of various types and structures. It is necessary to unify these heterogeneous data into a specific data model that can be used in knowledge graph. In the meantime, the data storage system stores data in the database to support efficient data access and query.

In the data processing stage, controlling data quality through data cleaning can establish a solid data foundation for subsequent data analysis and application. Through data fusion, the integration and association of multi-view heterogeneous data can be completed. In this way, data fusion and association between cross-system data, between stock data and incremental data, and between unstructured data, semi-structured data and structured data can be realized. Facing quality problems such as data loss and redundancy caused by the automatic data collection process, it is necessary to establish data inspection rules, including accuracy rules (rules related to value length, range, number, etc.), consistency rules (rules related to format specification, repetitive data, data type, primary key, etc.) and integrity rules (rules related to null value, relevance, etc.). On the basis, field filtering is carried out through critical similarity rules combined with a small amount of human intervention to realize redundant removal of duplicate data. Finally, the missing data filling and error correction are realized through the fuzzy matching rules of master data.

In the data storage system, the Hadoop cluster managed by Zookeeper ensures high availability of the system, and HDFS is used to store the acquired original files. The multi-copy storage strategy of HDFS ensures the fault tolerance of the data. Databases such as HBase and MongoDB are used for distributed storage to improve the efficiency of reading and writing unstructured and semi-structured data. In addition, For the processed data, Oracle or MySQL database is used to better support the display query of the front page, and Redis memory storage is used to enhance the response speed. Finally, in the stage of constructing knowledge graph, Neo4j graph database is used to store triplet data. In general, by integrating and storing data, the data management layer lays the foundation for subsequent data evaluation and knowledge reasoning, thereby supporting data-driven decision-making. This layer also improves the efficiency of the entire knowledge graph reasoning framework by optimizing data management, improving data utilization efficiency, reducing management costs, and protecting data security.

3.3. Manufacturing Knowledge Reasoning Layer

Based on the data cleaned, processed and stored by data management layer, knowledge reasoning layer handles in-depth analysis, modeling of the data and knowledge reasoning, so as to discover the potential knowledge in the data and discover the internal relationship between the data. Through knowledge reasoning, existing knowledge fields can be expanded, new knowledge can be discovered, and the value of data can be further enhanced.

Data modeling is used for further processing and analytical modeling of data. Specifically, operations which include cleaning, text segmentation, part-of-speech tagging, etc. are performed on the obtained corpus data. Then The word vector is generated from the word segmentation result through the word vector model, and the entity and relation are extracted for the construction of knowledge graph. on this basis, artificial intelligence algorithms are used to train and apply classification models, syntactic analysis models, and anaphora resolution models. Data modeling can be divided into the following five modules: A. corpus preprocessing: include corpus cleaning, word segmentation, part-of-speech tagging, stop words removal, etc. B. feature engineering: represent the word segmentation as a type that can be calculated by a computer, usually a vector. C. feature selection: select appropriate and expressive features, including entity recognition and keyword extraction. D. model training: use a variety of machine learning models and deep learning models to train models. E. model application: use machine learning algorithms to automatically classify texts by training classification models, and use deep learning algorithms to mine deep information such as syntactic structures and dependencies.

The data analysis module is mainly responsible for in-depth analysis of the data and exploring key features, patterns and rules in the data. This includes descriptive analysis, predictive analysis, and relevance analysis, etc. Related algorithms used in this module include natural language processing algorithm, deep learning algorithm, statistical algorithm, and representation learning algorithm, etc. Data analysis engines are also established, including knowledge reasoning engine, graph computing engine, rule inspection engine, and semantic search engine, etc.

The knowledge reasoning module is responsible for inferring existing knowledge and generating new knowledge. Applications of knowledge reasoning include entity prediction, link prediction, relation prediction, graph completion, and triplet classification. The knowledge reasoning methods used are divided into four types: reasoning based on rule representation, reasoning based on distribution, reasoning based on neural network and hybrid reasoning method. Through knowledge reasoning on manufacturing data, we can discover key factors affecting product quality, thereby optimizing the production process, improving product quality, and improving production efficiency. Moreover, knowledge reasoning can help decision-makers better understand data and information to make more accurate and rapid decisions. For example, through knowledge reasoning, the fault of the production line can be predicted, so that the maintenance can be carried out in time before the failure occurs, and the loss caused by shutdown can be avoided.

3.4. Application Layer

Knowledge reasoning is a key method to enhance the value of manufacturing data, which can help manufacturing industry better understand and use data. Knowledge reasoning can be applied to various scenarios in the intelligent manufacturing field: A. intelligent question and answer: Q&A takes natural language questions as input, queries the corresponding answers from the manufacturing knowledge graph, and returns them to the user in the form of text. B. product recommendation and expert search: compared with traditional recommendation systems, product recommendations based on knowledge graphs can establish relationships between users, between products, and between users and products, and it is easy to mine user groups and product groups with high similarities to achieve accurate push. Expert Search based on the knowledge graph can perform semantic analysis on user's questions, predict the professional skills required for the questions, and infer the set of experts matched by the user's questions. C. potential customer identification and risk analysis: potential customer identification based on knowledge graph can represent attribute characteristics of users and complex relationship between users, so as to achieve more accurate potential customer identification. Enterprise risk analysis based on knowledge graph can establish knowledge graphs among customers, enterprises and industries, in order to predict the risks faced by industries or enterprises from the perspective of industry associations and provide assistance for managers' decision-making. D. knowledge discovery and fault analysis: fault analysis based on knowledge graph expresses the linkage between fault events and their corresponding components in the form of graph structure, so as to locate the failure location, cause and treatment plan of the system accurately. E. digital twin and smart factory: the manufacturing process can integrate digital twin technology across various stages to simulate, evaluate and optimize the production process (Ren et al., 2020). Digital twin technology based on the knowledge map can be applied to the digital twin body construction and update, twin data fusion and analysis process in the digital twin technology (Li et al., 2021), so as to provide users with more intelligent and personalized service applications. In general, the application layer transforms the knowledge obtained from the previous layer into practical applications and services, so that the knowledge graph can truly serve businesses and users.

4. Conclusions and Future Work

To address the problem of multi-view data modeling and knowledge graph reasoning in the manufacturing field, a knowledge graph reasoning framework for manufacturing multi-view heterogeneous data is proposed in the paper. This framework is divided into manufacturing data acquisition layer, manufacturing data management layer, manufacturing knowledge reasoning layer and application layer. A management and analysis framework for multi-view data is designed, providing a systematic solution for manufacturing knowledge modeling and reasoning. The framework offers a crucial theoretical foundation for the construction of the manufacturing data intelligent governance model.

There still exist potential improvements to the methods, including an enhanced design of multi-view data reasoning model. Therefore, the following aspects of future work will be key points.

(1) Advanced knowledge reasoning techniques: models based on graph neural networks and models based on multi-view graph embedding are worth exploring deeply. These techniques can enhance inference capabilities and enable more accurate predictions and decision-making.

(2) Application in specific manufacturing domains: The framework can be further specialized and tailored to specific manufacturing domains. By incorporating domain-specific knowledge and ontologies, the framework can provide more targeted and domain-relevant insights and reasoning capabilities.

Funding

The research is supported by the NSFC (National Natural Science Foundation of China) project No.62225302, 92167108 and 62173023.

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