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Review

A review of industrial big data for decision making in intelligent manufacturing

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A B S T R A C T

Under the trend of economic globalization, intelligent manufacturing has attracted a lot of attention from academic and industry. Related enabling technologies make manufacturing industry more intelligent. As one of the key technologies in artificial intelligence, big data driven analysis improves the market competitiveness of manufacturing industry by mining the hidden knowledge value and potential ability of industrial big data, and helps enterprise leaders make wise decisions in various complex manufacturing environments. This paper provides a theoretical analysis basis for big data-driven technology to guide decision-making in intelligent manufacturing, fully demonstrating the practicability of big data-driven technology in the intelligent manufacturing industry, including key advantages and internal motivation. A conceptual framework of intelligent decision-making based on industrial big data-driven technology is proposed in this study, which provides valuable insights and thoughts for the severe challenges and future research directions in this field.

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1. Introduction

In the era of big data, the massive amount of big data generated by the manufacturing industry has the characteristics of an ultra-high dimension [1]. How to deal with these ultra-high dimension data, tap its potential value, and develop a data flow model suitable for the new manufacturing environment is a challenging problem [2]. At present, the big data-driven analysis will bring more ideal benefits to the manufacturing sector with the mutual support of related emerging technologies under the background of Industry 4.0. The data analysis process aims to improve the transparency of decision-making [3]. The decision-making based on big data-driven analysis maximizes the function of the whole manufacturing system according to the internal structure of the enterprise. It makes effective use of manufacturing resources to ensure the maximization of its economic benefits.

In the era of intelligent information interconnection and knowledge drive [4], big data sets off a wave of the digital revolution. Solutions based on big data analysis and intelligent computing are gradually used to reduce the complexity and cognitive burden of processing large amounts of data [5]. The company increasingly adopts a strong strategy driven by data to improve its competitiveness [6]. Big data-driven technology provides an excellent opportunity for today's manufacturing mode to transition from traditional manufacturing to intelligent manufacturing. In recent years, with the smart development of industrial factories,big data analysis has become the main driving force for enterprises to provide industrial value, making industrial production more intelligent. The data collected from various sources have been applied to industrial production research. Production research enabled by data has shifted from that based on analytical models to data-driven [7].

Big data analysis is a revolutionary leap in traditional data analysis. The characteristics of big data can be summarized and defined by 5 V as shown in Fig. 1 [1,8,9]: high capacity (a large amount of data), high speed (data generated and updated at high speed), high diversity (data generated by various sources appear in different forms), high accuracy and high value (tremendous potential value hidden in data). In the era of big data in the manufacturing industry, the unique characteristics of big data systems are real-time, dynamic and adaptive [10]. Compared with the traditional data analysis system, the data managed by a big data platform comes from the physical entity world or virtual digital world. Owing to the variety of data sources, the ability to process data efficiently highlights a more excellent prospect. The manufacturing industry is undergoing revolutionary information and intelligent transformation [11]. It is imperative to provide on-demand communication services to ensure high reliability, robust scalability, and availability of manufacturing systems.

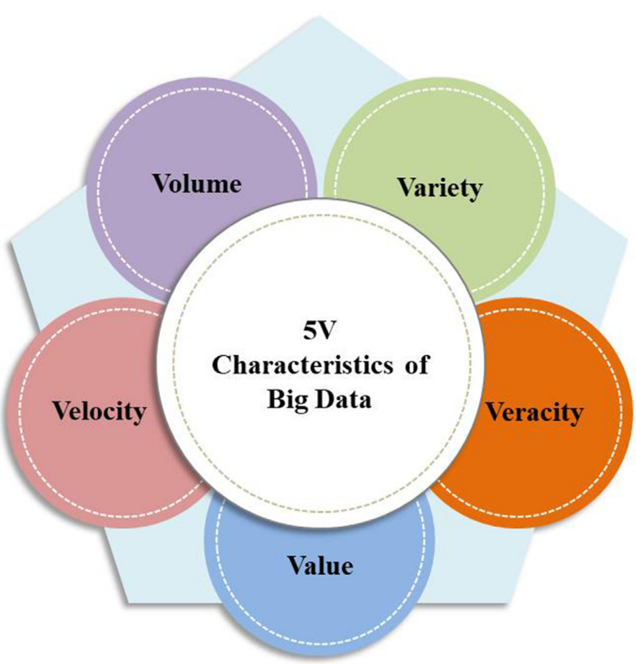

Fig. 1. 5 V characteristics of big data.

Intelligent manufacturing covers many aspects of the manufacturing field, not only a technology but also the integration of all aspects of manufacturing field and information technology, aiming to convert data acquired across the product lifecycle into manufacturing intelligence in order to yield positive impacts on all aspects of manufacturing (such as intelligent products, intelligent production, intelligent services, etc.). Big data can create real-time solutions to meet the challenges of all walks of life [12]. Big data-driven methods will have an impact on the quality management of production systems. Mining and analyzing data related to product quality can provide decision support for quality control and guarantee in the manufacturing system. Intelligent manufacturing aims to build a highly integrated collaborative production ecosystem, which can respond to the dynamically changing demands and environmental conditions in the whole value chain in real-time. The core of intelligent manufacturing lies in the interconnection and deep integration between the physical world and the digital world [13]. The strategic focus of the contemporary manufacturing industry is integrating advanced digital information technology into various application fields of the manufacturing industry. With the advent of Industry 4.0, multiple aspects of manufacturing production and value creation processes and business models have undergone tremendous changes. Manufacturing companies of all sizes worldwide continue to develop in the direction of intelligence, and formulating a reasonable and efficient digital strategy will steadily boost their competitive advantages.

With the further development of data storage and analysis technology, big data-driven analysis is an essential driving force for creating the primary value of the manufacturing industry [14]. Leaders' decision-making methods are also continually changing, relying mainly on big data analysis rather than experience to create more manufacturing value. Big data-driven technology provides a broad prospect for the manufacturing industry and lays the foundation for sustainable manufacturing in the future [15], promoting the practice and development of Industry 4.0.

In today's competitive contexts, companies are interested not only in understanding the technical aspects of big data analytics (BDA) but also, and increasingly, in learning how to exploit the knowledge and insight-creation potential of the data they possess, and to effectively use this knowledge within their strategic and operative decision-making and innovation processes. Big data has already been a research hotspot in intelligent manufacturing. [16] concerned the interconnections between big data (BD) and co-innovation and used BD as a common perspective of analysis as well as a concept aggregating different research streams (open innovation, co-creation and collaborative innovation). [17] investigated the role of the Internet of Things (IoT) and Big Data in terms of how businesses manage their digital transformation. [18] presented the recognition and challenges of the big data and the microgrid, and summarized enhancement areas in the microgrid like stability improvement, asset management, renewable energy prediction, and decision-making support. [19] offered an analysis of relevant standards for manufacturing systems which was performed for the Digital Manufacturing Platforms (DMP) cluster in order to identify those standards that might be relevant for Zero defects manufacturing(ZDM), as well as for further projects or manufacturing platform designers. [20] highlighted how reliability can be used to support different types of strategic decisions in the context of Industry 4.0 and introduced the need for research associating management decisions with the technologies of Industry 4.0. However, to date there is no systematic review concerning the relationship between intelligent decision-making and big data(BD) in manufacturing. We aim to fill this gap, pointing out how the effective exploitation of big data analytic capabilities (BDAC) is crucial for implementing successful decision-making within intelligent manufacturing.

The main contributions of this paper are as follows:

- This article presents the systematic overview of industrial big data for intelligent decision-making, and introduces the application of big data-driven technology in intelligent manufacturing.
- This study provides a theoretical analysis basis for big data-driven technology to guide decision-making in intelligent manufacturing, fully demonstrating the practicability of big data-driven technology in the intelligent manufacturing industry, including key advantages and internal motivation.
- This paper puts forward an intelligent decision analysis framework based on industrial big data-driven technology and introduces the core design concept of this framework.
- This method develops a brand-new intelligent manufacturing paradigm, which focuses on real-time dynamic perception and accurate decision-making based on big data-driven analysis in manufacturing environment.
- This article aims to introduce the role of big data-driven technology in the field of intelligent decision-making in manufacturing.

The rest of this paper is organized as follows: Section 2 provides the overview of industrial big data for decision making in intelligent manufacturing. The application of big data-driven intelligent manufacturing is discussed in Section 3. Section 4 presents the challenges of industrial big data in intelligent manufacturing. Section 5, a conceptual framework of intelligent decision-making analysis based on industrial big data-driven technology is proposed. Finally, conclusions and future research are drawn in Section 6.

2. Overview of industrial big data for decision making

2.1. Architecture and component mechanisms of big data-driven platform

At this stage, data acquisition system, Internet of Things and Cyber-physical System are applied to industrial processes. A large amount of data is collected and stored in industrial databases. Therefore, the scale of the entire industrial data is continuously expanding and has entered the era of big data. Generally, most process data are detected and acquired in a noisy environment, which indicates that the detected data will be affected by a random noise environment. In the industrial process, the input data of the prediction model is often the process data obtained by rapid sampling, and the output is usually the critical factor variable of quality. However, in reality, only a few data sets in the industrial process are marked, and most data are often missing marks. These unlabeled data may also contain a large amount of process information, which will make an essential contribution to the modeling. To address this problem, some organizations are implementing semi-monitored modeling methods into industrial process data analysis, maximizing the value of all the data obtained, including tagged and unlabeled data. However, a series of modeling methods, such as semi-supervised probabilistic principal component regression (SSPPCR), are limited to small data sets and are not suitable for large data sets that are increasing every day. MapReduce framework is used to deal with the distributed parallel modeling of industrial big data quality prediction. The traditional SSPPCR model was deployed on the MapReduce framework through training, learning, and decision-making of a distributed parallel model [21]. This distributed parallel modeling method has substantial advantages in big data quality prediction. It can also be extended to many real-time large-scale data sets that need to be processed. Intelligence manufacturing is the technology utilizing interconnected machines and tools for optimizing manufacturing performance [12].

From the perspective of inclusiveness, the inclusive model of production and consumption can be interpreted as functional redistribution, which shows the redistribution of functions between enterprises and stakeholders. "Redistribution" means that consumers show higher participation in the design and production process. Seven requirements of big data processing process in the manufacturing field are put forward [22]:

- Provide an extensible method to distribute and configure sensor equipment throughout the manufacturing process, and store data in descriptive processes and models.
- Provide methods to detect and troubleshoot sophisticated manufacturing events/ production methods in the deployed sensor data stream.
- Provide methods for storing real-time data, and perform correlation analysis on big data sets and data streams according to specific dimensions.
- Provide methods to adjust and adapt to complex event prediction models continually.
- Provide the method of creating an alarm prompt as the expected deviation response to the planned production/ manufacturing target based on calculation analysis.
- Provide suggestions and automatic decision-making methods to reduce production manufacturing errors.
- Provide the method of actively adapting to the production process based on calculation and analysis.

Due to globalization and the increasing demand for small-batch customized products, the manufacturing operation activities are becoming more and more dispersed. Many forms of manufacturing research appear to be service-oriented. To increase the business cooperation efficiency of manufacturing companies and shorten the product development cycle, Lu et al. [23] discussed some challenges in developing cloud-based manufacturing equipment and supporting technologies. It proposed a general system architecture of cloud-based manufacturing equipment under the Cyber-physical production system and big data analysis. This architecture connects manufacturing equipment to the cloud to provide on-demand manufacturing services that easily customize and optimize output to meet target needs. A conceptual framework of big data analysis was developed to analyze the impact of big data on manufacturing redistribution [24], create common value, and make the manufacturing value chain more inclusive. In the era of big data, the decision-making of supply chain management is increasingly driven by data rather than traditional experience. A decentralized data distribution architecture was applied [25], which used the fog computing paradigm to improve the potential availability of data. End-to-end engineering of the whole product life cycle refers to integrating and digitizing the data generated in each stage of the product life cycle to create new knowledge related to the product life [26], which involves the decision-making process from production to supply and operation.

2.2. Processing of industrial big data

2.2.1. Sources of industrial big data

All industrial big data in the product lifecycle includes product design, manufacturing, supply chain, marketing, and customer feedback. According to the data source, industrial big data is divided into system data (data generated from various enterprise information systems) and IoT data (data captured by sensors, such as radio frequency identification readers and barcode readers). The primary sources of industrial big data are shown in Fig. 2. Embedding sensors in smart devices collect a large amount of industrial process data about shop floor equipment and product status. The manufacturing industry often represents a production and operation environment with prosperous data [26], which continuously generates more and more complex data in the manufacturing process. Still, leaders only use a small part and do not maximize the whole data value system's function. There are many sources of big data, such as e-commerce applications, shopping records, banking transactions, social networks, networked devices, and sensors, etc. At this stage, products are typically equipped with sensors and related sensing chips, which are convenient for reporting the real-time status of the product to the manufacturer or customer to jointly create the Internet of Things (IoT). In many advanced manufacturing environments, data sources are transmitted to decision-makers almost in real-time and provide more opportunities to know the potential operation modes of enterprises at all times, which is convenient for making real-time decisions [27]. Big data in manufacturing usually refers to massive data generated from the product life cycle [28], including design, production, etc. The data sources in manufacturing are typically divided into the following aspects:

- Manufacturing resource data: real-time performance data of smart devices collected through the industrial Internet of Things technology, production data in its service system.
- Manufacturing systems and computer aid data include product design, order configuration, material allocation, production planning, business management, etc.
- Internet data: Open websites such as public government social services sites, e-commerce platforms (Wal-Mart, Amazon, etc.), social networking platforms (YouTube, Facebook, Twitter, etc.).

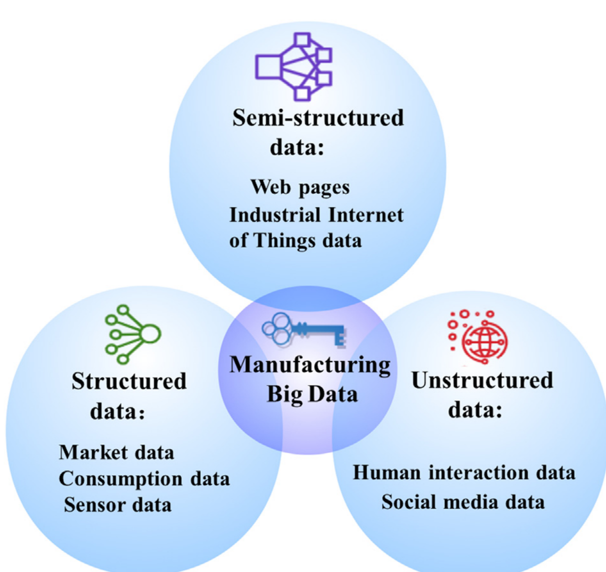

Fig. 2. Sources of industrial big data.

Usually, a large amount of industrial raw data is not much practical use. The original data has multi-source, heterogeneous, multi-scale, high noise, and other characteristics must be processed and analyzed for value extraction. First, collect data from data sources in various ways, such as API (Application Programming Interface), Web Crawler, IoT (Intelligent Sensor and RFID), and then mine and analyze real-time and historical data through a series of new information technologies (such as machine learning, deep learning, etc.). The analysis of industrial big data can play a leading role in the concept of intelligent manufacturing only when it transits from structured, static mode and centralized to mixed structured, dynamic mode and distributed [29]. Browsing data requires advanced data analysis, and information knowledge can be extracted from big data through advanced analytics [30], methods, and tools such as machine learning and predictive models. In intelligent manufacturing, the information knowledge of manufacturing comes from industrial big data analysis, and the characteristics of data analysis enhance the manufacturing competitiveness in the global market.

2.2.2. Acquisition and transmission of big data

With the continuous growth and improvement of modern factories, many data recording historical manufacturing processes are captured and retained by a large number of sensors to describe the past manufacturing behavior process. It is usually analyzed and evaluated with advanced process monitoring technology to explain the historical manufacturing process's trend development information to engineers. However, the best monitoring technology process needs to sort out the data and group them into classes before analyzing them. It takes a lot of resources to create these classified data groups. Only the fault state can be found as a result of execution, which lacks the understanding of the manufacturing process. The related research was carried out on the industrial separation tower [31]. The essential process trends of high-dimensional and multivariate manufacturing data were described by the data clustering algorithm and feature extraction. Bevilacqua et al. [32] aimed at integrating the factory's existing information systems and IoT-based energy management, a data analytic architecture was developed to collect data from different sources to improve energy-aware decision-making, the proposed approach supports intelligent factories' development from an energy perspective by improving the overall equipment efficiency and productivity of machine tools in manufacturing.

Data collection for different granularity levels, context-aware data analysis, and evaluation based on historical and real-time data [26]. The output forecast data triggers the system self-coordination mechanism to play the functions of reconfiguration/allocation and self-adjustment to reduce the frequency of manufacturing failure events. Data storage and information acquisition are of vital significance to enterprises. When users store and use data, the data storage mode supported by storage providers is clear and the core technology is usually not leaked. However, this storage service is often not safe enough. It is easily affected by many factors, such as access rights, software, and hardware failures and system instability, resulting in collapse and economic loss of data abuse. The issues related to data confidentiality and security are attracting more and more attention from relevant personnel. Redundant Residual Number System (RRNS) was used to divide user data files into several replicable blocks and distribute them in parallel to the storage providers of hybrid multi-cloud (private cloud, public cloud, and hybrid cloud) storage providers [33]. Since each cloud storage provider cannot rebuild and split uploaded data, the system is an essential guarantee of the reliability of data replication storage. It guarantees data privacy and confidentiality through data obfuscation and encryption strategies. In the process of prediction modeling of sensor data, due to the noise of these data, there may be problems such as data transmission, measurement error, technical detection, and so on. The anomaly detection method is usually used to monitor abnormal data which deviates from the expected trend. A semi-supervised method is used to deal with lost and unmarked data. However, these methods are not suitable for online anomaly detection, and can not solve the problems of missing data and noise in real-time. Corizzo et al. [34] provided an online real-time data anomaly detection framework and a novel anomaly detection strategy. Firstly, the stacked automatic encoder is trained with standard data, and the projection of the test data in the encoder is compared with its close standard data. The method based on distance detection and dynamic learning can realize multi-target data anomaly detection, predict the value of target variables and target time range, and locate the data source position in real-time. New generation industries rely on big data to improve work efficiency. Smart nodes collect big data and transmit it to the cloud wirelessly. However, the size of the smart nodes is limited. Kong et al. [35] proposed a compressive-sensing-based collection framework to reduce energy consumption, which could minimize the amount of collection while ensuring data quality and productivity.

2.2.3. Storage and analysis of big data

The manufacturing industry often represents a production and operation environment with prosperous data, which continuously generates more and more complex data in the manufacturing process. In reality, leaders use only a small portion and do not maximize the overall data value system. The analysis and evaluation of the data extracted directly from the workshop may be deviation, measures should be taken to prevent abnormal conditions effectively, and human intervention is triggered through self-coordination mechanisms or alarms to restore normal execution [26]. The intelligence of the manufacturing system depends on the ability to accumulate and analyze big data. Big data analysis can improve customer service, enhance product quality, and create more value for enterprises.

Big data decision-making ability directly determines the quality of manufacturing decision-making. The least-square method was used to test the influence of big data decision-making ability on decision-making quality [36]. The results show that big data analysis is a crucial prerequisite for big data decision-making ability. Big data analysis refers to the process of collection, management, processing, analysis, and visualization. Data is collected by temporary and persistent storage under the big data-driven technology in the network manufacturing system [37]. Big data decision-makers can make decisions based on "known knowledge information" instead of "their imagination" and enhance and improve the knowledge system formed [36]. The effectiveness of decision quality can be analyzed and evaluated by decision-makers' satisfaction degree to achieve the expected results. Big data is a term used to describe the massive volume of both structured and unstructured data that is too large that it is difficult to process using conventional database and software techniques. Although Big Data is in its early stages, it has remarkably transformed every sector in the industry. It has also revamped the Supply Chain Management giving it a new dimension by increasing efficiency of production and optimization of operations. Delphi technology was used to identify the related problems of supply chain management and solve these problems by integrating big data analysis [38]. The popularity of big data is generally considered as a supplement to management processes in various industries. Big data analysis can improve operational and enterprise strategic capabilities, such as business analysis, supply chain management, and industrial processes, and become vital in supply chain management [39]. Real-time process monitoring integrated with IoT sensors and big data analysis, Shah et al. [40] developed a data-driven predictive model using the frequency domain representation of vibration signals to infer key process monitoring variables.

The analysis of a large number of manufacturing data can expand the knowledge base and improve the decision-making for different manufacturing stages [29]. Big data analysis enhances customer service and product quality and creates more value for enterprises [27]. The quality of data-driven decision-making depends not only on the data itself but also closely related to the process of data acquisition and analysis. Only digging out the real relationships hidden in the data can play an essential role in the manufacturing industry [36]. The data mining tool is an effective method to analyze and process data to access all data sites for multidimensional analysis and decision support [41]. Data integration expands the data set's dimension, mainly for establishing a standard data structure to facilitate processing. When the aspects of data generated by the manufacturing process increase sharply, processing large data sets in an acceptable time range are the main focus of big data analysis. A shared data-driven factory model was applied to deal with industrial production big data [42]. This model covers the data capture, transmission, integration, storage, and analysis processes. Its basic principle is to promote data exchange between data providers and data users, analyze data by batch processing in a distributed way, and commit to data interoperability and standardization. Industrial big data, organized somehow through analytics, can be a valuable resource for enterprises to create value. The analysis of big data information has gradually become the strategic focus of enterprises. In a sizeable data-intensive environment, leaders, and external organizations' decision to establish a collaborative network has a positive impact on corporate performance [43]. Big data analysis is also an intangible resource. It no longer guides work based on experience and intuition but is a kind of ability to develop, explore, accumulate, share, and transform information and knowledge to guide decision-making. Stimulate more decision-making creativity and creative thinking, and the strategic goal of using big data tools effectively will create sustainable competitive advantages for companies.

2.2.4. Mining and visualization of big data knowledge rules

One of the main challenges of big data analytics is the visualization of results to support decision-making at all levels within the manufacturing industry [29]. High-level decisions are usually made in uncertain situations based on the leader's experience and knowledge [44], leaving a significant gap in the space to be made. The ability of enterprises to adapt to market changes determines the development of the market economy. The dynamics and flexibility of the manufacturing industry improve their competitiveness, and the constant evolution of manufacturing network structure is also a considerable challenge. The origin of the decision-making task is the manufacturing internet, industrial manufacturing process, and rational allocation of resources, requiring full preparation, logical analysis, and continuous development of real-time evaluation schemes to make effective decisions.

The key element of Industry 4.0 is the collection, evaluation, and quantitative analysis of industrial data. At present, digital intelligent manufacturing equipment and automated production lines have been widely introduced to complex product manufacturing enterprises [45]. Generally speaking, due to the high cost of data acquisition, the real-time dynamic data acquisition methods in some highly complex production environments are partially limited to RFID (Radio Frequency Identification) technology, which can't evaluate the production process in real-time and efficiently, and it takes too long to rely on the real-time database. The multi-mode data collection method was adopted to make up for the limitations of traditional semi-automatic technology [46]. In the production process, the concept of digital twin (DT) is taken to make the production entity system and digital-analog system couple equivalently, reduce the time delay of information transmission, ensure the consistency and unity of the process, and allow real-time production control to enhance the visual transparency of information to fully support the strategic production plan and operation plan of the enterprise.

2.3. Design and implementation of big data-driven system in intelligent manufacturing

Big data systems typically consist of six necessary subsystems: data generation, data acquisition, data transmission, data processing, storage, and analysis methods [14]. A new intelligent factory framework with independent agent function and integration of feedback and coordination of big data analysis was investigated [47]. The framework organically combines industrial network, cloud and supervision and control terminals with intelligent workshop objects (machines, conveyors and products, etc.), and divides intelligent object modeling into four types of agents, the process works efficiently through autonomous decision-making and distributes cooperation among agents, defines a central coordinator in the cloud for feedback and coordination, and proposes an intelligent negotiation mechanism to facilitate inter-agency collaboration. Four complementary strategies are designed to improve the agent's decision-making and the coordinator's behavior to prevent system deadlock. To verify the feasibility and effectiveness of the proposed negotiation mechanism and the deadlock prevention strategy, two different kinds of product processing simulations are used. It shows that the implementation of smart factory can effectively avoid deadlock caused by multi-operation types and multi-function agents and can dynamically deal with various product types. However, a smart factory prototype was not built to optimize overall system performance based on system-wide feedback and coordination for big data analytics.

Because big data is challenging to maintain, expand and collaborate, it isn't easy to control the operating costs of companies participating in the supply chain, Lu et al. [48] developed a four-level expandable cloud platform to realize collaborative service in the supply chain, and constructed a collaborative services model from the perspectives of sales, procurement and manufacturing can achieve the exchange of data, information and knowledge, thus improving the competitiveness of enterprises and reducing costs. Despite having played a vital role in the Industry 4.0 era, the Internet of Things is currently faced with many challenges of data collection, to fill this gap, Ji et al. [49] presented a heterogeneous device data ingestion model for industrial big data platform. Four key strategies of the proposed model, namely data indexing, data synchronization, data slicing, and data splitting, are utilized for ingesting multi-type and large-scale heterogeneous device data. This model has been verified on our industrial big data platform.

To better implement Industry 4.0, the underlying architecture of big data-driven platform based on CPS is shown in Fig. 3, which generally covers the following three characteristics [50]:

- Horizontal integration through value network: Promote efficient cooperation among enterprises, and form an efficient operation system through smooth integration and mutual correlation.
- Vertical integration and networked manufacturing systems: means a highly flexible, reconfigurable, intelligent factory. Dynamic configuration of production management, manufacturing, and control is realized through actuators and sensors. A large amount of data value information is collected and processed to improve the transparency of the manufacturing process.

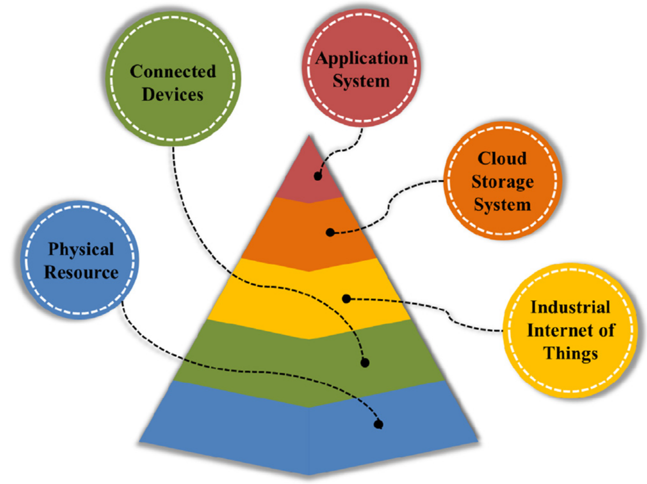

Fig. 3. Basic architecture of big data-driven platform based on CPS.

- End-to-end digital integration engineering of the whole value chain: the vertical integration setting is the factory, which supports product customization.

2.4. Model and algorithm of industrial big data-driven technology

Big data analytics is not a new concept. It comes from Internet companies such as Google, Yahoo, Amazon, and Netflix that want to improve supply chain performance by analyzing the market's big data qualitative analysis, which is not well used because of a lack of expertise. Table 1 provides a overview of approaches on Big Data.

Big data analysis in the manufacturing industry is mainly used to deal with massive data in various manufacturing activities, which has dramatically exceeded conventional data processing systems' capability. Big data analytics is becoming increasingly popular among manufacturing companies [60]. It is challenging to collect unstructured data, which usually comes from the Internet, event logs, multimedia social communication, etc. and needs innovative, practical technologies to capture, process, and manage them. Vafeiadis et al. [61] used the latest techniques and methods from big data analysis, deep learning, and prediction. Most manufacturing workshops use the same sensors, and they provide similar data in the virtual workshop. The decision support system is designed to adapt to the manufacturing environment. The digital factory model (DFM) integrates the manufacturing information and knowledge about products and machines.

In order to improve the manufacturing capability, [62] proposed a method of intelligent human computer interaction based on non redundant EMG signal. [63] put forward a deep learning framework for multi-modal fusion for multi-target object stoic grasping, and the success rate of the model was enhanced by combining multi-scale candidate boxes. [64] proposed an optimized particle filter using the maximum variance weight segmentation resampling algorithm. [65] presented a TDE-based SMC to realize the decoupling control of the multi-arm space robot system. [66] put forward an effective algorithm to plan the near-optimal joint configurations for the pregrasping cages.

The need and potential benefits for the combined use of simulation and big data in intelligent manufacturing has been widely recognized. [67] proposed a novel method for the holistic, simulation driven ship design optimization under uncertainty in the big data era. [68] put forward a method of simulation for big data system based on Markov model and IoT system. [69] introduced Bayesian hierarchical modeling to dimension expansion, which originally has only been modeled using a method of moments

Table 1
Overview of approaches on Big Data.

Reference	Method/Model	Application	Description
Zhang et al. [51]	Fuzzy DEMATEL (Decision Making Trial and Evaluation Laboratory)	Product service system	Provide some reference value for upgrading and supplementing the smart manufacturing architecture
Zhou et al. [52]	Generative Adversarial Net-works(GAN) and aided by Gaussian Discriminant Analysis(GDA)	Industrial big data environments	Enhance the fault classification accuracy
Chitrakant et al. [53]	Cuckoo-Grey wolf based Correlative Naive Bayes classifier and MapReduce Model (CGCNB-MRM)	The classification of big data	Perform the classification for each data samples based on the probability index table and the posterior probability of the data
Madhu et al. [54]	Probabilistic feature Patterns (PFP)	Efficient data integration and utilizing	Index the unsupervised multiple heterogeneous integrated cluster data sources
Alguliyev et al. [55]	Davies-Bouldin index	Apply to expert systems to help experts make group decisions based on several alternatives	Assign weights to single clustering methods using the purity utility function
Badr et al. [56]	Predictive model with Matrix factorization and random forest	Big Data recommendation systems	The model is able to significantly speed up the distributed training, as well as improve the performance in the context of Big Data
Yu et al. [57]	K-type clustering algorithm	Cluster hybrid matrix-object data	Define a new dissimilarity measure between two numeric matrix-objects
Ada et al. [58]	IDEAaS (Interactive Data Exploration As-a-Service) approach	Big data management	Provide summarised representation of collected data streams
Jain et al. [38]	Delphi technique	Big data in supply chain management	Identify the issues regarding Supply Chain Management by employing Delphi technique and aim to resolve them by incorporating Big Data Analytics
Zhuang et al. [59]	Artificial bee colony algorithm	Open shop scheduling	Achieve the best results in large-scale problems

approach and combined dimension expansion with a spectral method to model big non-stationary spatial fields in a computationally efficient manner. [70] developed a decision support system, which consists of a big data warehouse and a simulation model. The former stores and provides integrated real data to the simulation model, which models the respective materials and information flows. [71] developed a novel CAD-based simulation model for manufacturing of spiral bevel gears by face milling. This model achieved the 3D kinematic simulation of both face milling and face hobbing processes, generating the undeformed solid chip geometry as well as the simulated tooth solid geometry of a spiral bevel gear pinion and a spiral bevel gear wheel as an output. [72] presented a well-distributed volumetric heat source model for numerical simulation of wire arc additive manufacturing process. [73] put forward a simulation–optimization approach for adaptive manufacturing capacity planning in small and medium-sized enterprises. The approach includes an artificial neural network for model simulation and data relationship recognition, combined with a genetic algorithm for optimizing manufacturing resource configuration. [74] developed a hierarchical model to incorporate reference measurement uncertainty and effects of different imaging thresholds for both experiments and simulations. [75] presented an optimally-coupled multi-time stepping method for transient heat conduction simulation for additive manufacturing. This allowed numerical stability of the multi-time step model, even with disparate materials or meshes on either side of the subdomain interfaces. [76] introduced a framework for a simulation-based assessment of quality inspection strategies and effect analysis of error classification on the overall manufacturing system with regard to selected key figures.

To maximize profits, enterprises apply intelligent technology to traditional manufacturing industries. A service framework based on big data-driven forecasting was proposed [77], which includes the information perception layer, information application layer, and big data service layer. This framework can support the decision-making of reducing costs and provide an effective method for the product-service system. Although there are many kinds of data, the amount of data generated is enormous, and the speed of obtaining data (big data) is very fast, the quality of big data is far from perfect [78]. Data mining technology can model, classify, and aggregate a large amount of data and discover the correlation between data [79]. The use of real-time optimal decision analysis to solve decision-making problems [80] increases complexity and data volume. Various studies are being carried out in this direction to meet the complex big data challenge. A hybrid linear planning model is established to achieve the best results in large-scale manufacturing databases through improved artificial bee colony algorithms [59]. Galletta et al. [81] focused on the customer loyalty program and proposed ‘retention’ marketing strategies that used cloud-based software as a service model to store and analyze big data related to purchases and products’ level for providing customers with a list of recommended products to maximize revenues. The Internet of Things makes pervasive computing become the connectivity of various applications deployed globally by expanding the Internet [82].

The aggregation of large-scale data from multiple sources, such as the Internet of Things, social media, and search engines, has provided business-to-business marketing organisations with the ability to provide online analysis of the planning approach for business development [83]. Explore the implicit relationship between big data, programmatic marketing, and decision marketing in the industry by relying on big data-driven technologies. A characteristic feature of multi-criteria decision analysis (MCDA) assessment of sustainable manufacturing is the involvement of decision-makers or experts (to varying degrees) (including defining the importance or “weight” of each standard). However, the cost is usually high. The typical MCDA method is generally carried out for one standard. The biggest disadvantage is that the range of weight sensitivity analysis is limited, and it is difficult to show the “full picture” of the decision space. Orderly combination sorting is carried out by four predefined weight distribution objectively set standards [84]. This solution provides a fast, reasonable, and systematic method for data mining and provides a broader and more accurate insight into the decision space considered.

The combination of mobile computing and cloud puts forward a new mobile cloud computing paradigm, Tawalbeh et al. [85] proposed a useful hybrid mobile cloud computing model, which combined the concept of centralized and collaborative methods, using cloud computing for big data analysis. The hybrid cloud model with the mobile cloud computing simulator is 75% higher than the traditional cloud model. The manufacturing system based on Industry 4.0 is characterized by self-optimization, self-learning, and self-training. At present, advanced intelligent machines are widely used in manufacturing systems. The research solved the two-objective random flow shop scheduling problem and established a mixed-integer programming model with the least programming time and delay time as an excellent optimizer to solve the problem [86]. At the same time, a pyrotechnic algorithm and an explosion spark program were built to help engineers and leaders make reasonable and efficient decisions. However, the cooperation and cooperative scheduling model of the manufacturing system was not thoroughly considered to meet the specifications of Industry 4.0 production system standards. The conceptual framework of big data analysis was put forward from the product life cycle perspective, creating the concept of sustainable intelligent manufacturing [87].

Big data analytics is expected to make an outstanding contribution to the development of intelligent manufacturing and promote the implementation of Industry 4.0. A statistical process monitoring (SPM) method based on process characteristics or functions was proposed to facilitate the centralized processing of various big data [88]. Real-time statistical analysis and online monitoring can realize high-speed analysis, autonomous cooperation, coordination, and decision-making mechanisms and strategies. The connectivity and responsiveness of the model were analyzed [89]. By establishing an accurate and flexible data-driven model for unique data, a new analysis method based on big data processing analysis and machine learning algorithms is provided. The proposed framework aimed to solve the threading function of five machine learning mechanisms for classification problems [90]. The hourly profit margin index was described as the target process control parameter in the process of industrial production. An agile control method was proposed to help make more effective operational decisions [3]. Big data technology has great applicability in the manufacturing industry, but its advancement has not been completely explored in many respects. It is the first attempt to examine the effect of big data on manufacturing companies' results by integrating decision-making and assessment tests [91]. The new hybrid method of DEMATEL-ANFIS was proposed to reveal the importance and dependence of big data on Malaysian manufacturing companies' performance. The research reveals that big data technology factors (perceived revenue, technical resources, big data quality and integration, complexity) have the greatest impact on enterprise performance, and are one of the pioneers of using DEMATEL-ANFIS method in big data manufacturing, highlighting the strategic potential of big data in manufacturing to a great extent. In order to alleviate the competitive pressure faced by enterprises, big data technology awakens enterprises' attention to customer relationship management. Fuzzy semantics and text mining technology are used to classify text data features [92]. A new text analysis model was proposed, which is convenient for enterprise leaders to make efficient marketing decisions. Fahmideh et al. [93] applied a goal obstacle analysis method that uses imperfect information to select architecture decisions, uses fuzzy logic analysis to rank candidate architectures, and finally finds the best structure to solve uncertain risks. To realize intelligent decision-making and adapt to the variability of conventional production hierarchy, more effective multi-criteria decision-making and new computer technologies are widely used in production strategies. Although existing research has developed many novel multi-criteria decision-making methods (MCDM), leaders face conflicts in relevant decision-making standards every day, Wu et al. [94] developed a verification scheme to check the effectiveness of the MCDM method, which was the goal of decision-making and study the influence of control variables (such as the existence of practical solutions, normalization methods, aggregation methods and interaction with decision-makers) on the effectiveness of multi-criteria decision-making.

Intelligent manufacturing has gained tremendous interest in both research and industry in the past few years. Over nearly the same period of time, machine learning (ML) has made phenomenal advancements, finding its way into many aspects of manufacturing. The application of the latest developments in the field of artificial intelligence has become quite common in real application decision support systems. Decision support systems can occur through the use of machine learning methods for different applications [95]. Machine learning (ML) is a subset of artificial intelligence (AI) and an applied computational technique with the ability to process and learn from large, complex and multidimensional data, to build predictive models [96]. Machine learning has become a hot topic in the field of industrial big data manufacturing, providing many useful tools for processing and analyzing machine data. Some learning algorithms and models have been applied in engineering cases, such as Support Vector Machine (SVM), Naive Bayes (NB), K-nearest Neighbors (KNN), Decision Tree(DT), Logistic Regression(LR), Deep Neural Network (DNN), Convolutional Neural Network (CNN) and so on. Support vector machines (SVM) is a method that is typically utilized for binary classification. [97] analyzed the performance in detection of internal defects, by means of training and operating Support Vector Machines (SVM) with thermal contrast information obtained from Background Thermal Compensation by Filtering (BTCF) technique. [98] analyzed data for defective products with the Particle Swarm Optimization (PSO) and Nave Bayes Classifier method. [99] provided a kNN-based (k-nearest neighbors) similarity method for rapid process diagnosis and process performance monitoring. [100] provided verification in the application of decision tree-based machine learning algorithms for optimal maintenance decision-making. [101] combined deep neural network (DNN) and Markov decision processes (MDP) for the dynamic dispatching of re-entrant production systems. [102] proposed a dynamic scheduling mechanism of part feeding for mixed-model assembly lines based on the modified neural network and knowledge base. [103] introduced MIGRATE (Machine learning for Smart Energy), a novel three-step framework to predict the machine-specific load profiles via energy disaggregation, which are in turn used to predict the machine's activity state and the respective production capacities. Machine learning (ML) played a significant role in the feasibility of advanced manufacturing. Various ML manufacturing implementations exist in similar fields including surface roughness predictions [104], control learning [105], parameter optimization [106], optimal class [95] and distortion prediction [107]. These proposed artificial intelligence algorithm illustrates the potential of machine learning methods in manufacturing applications. Machine learning (ML) have become topics of interest in process industry. Big data analysis and machine learning can help manufacturing systems perceive the environment, discover and identify information knowledge, and make decisions automatically.

3. Application of big data-driven in intelligent manufacturing

3.1. Intelligent decision-making and optimization of process flow

Big data analytics can create new competitive opportunities by extracting useful value and bringing advanced predictive insights into strategic process management, widely used in supply chain operations such as demand planning, procurement, production, inventory, and logistics [108]. Big data analysis can improve manufacturing systems and help enterprises make wise decisions, such as product forecasting, enterprise performance management, product design, customer service, and so on [109]. Big data can be used to improve the working efficiency of aging manufacturing systems. A new hierarchical dimension reduction method was proposed [110], and a probabilistic approach based on generalized distance measurement was developed to detect and avoid faults.

Defect recognition and scheduling techniques are vital to the big data driven decision strategy in intelligent manufacturing. [111] proposed an enhanced sparse representation-based intelligent recognition (ESRIR) method, which involves two stages of structured dictionary designs and intelligent defect recognition. [112] trained a defect high-precision recognition model to recognize surface defects and created to divide component surfaces and locate defects on the pieces of component surfaces. [113] proposed a semi-supervised learning method using the convolutional neural network for steel surface defect recognition. [114] developed a pattern recognition method of fault diagnostics based on a new health indicator for smart manufacturing. [115] presented a novel method of cost optimization for big data workloads based on dynamic scheduling and cluster-size tuning. [116] proposed efficient scheduling algorithms that reduce the cost of resource usage in a cloud-deployed Apache Spark cluster. [117] put forward a dynamic Spark memory-aware task scheduler (DMATS), which not only treats memory and network I/O as a computational resource but also dynamically adjusts concurrency when scheduling tasks.

To deeply understand the manufacturing process, it is necessary to use many process data analysis and knowledge mining to improve the safety and stability of the process, which is an essential guarantee for creating high-quality products. Many fault diagnostics and identification methods based on data rely on "supervised" learning. The output data need to be marked in groups, including normal, abnormal, or operating procedures. In the actual production workshop, it is a time-consuming and labor-intensive task to efficiently and accurately mark real-time manufacturing data due to the complicated manufacturing environments and complicated interference factors [46]. Unsupervised learning includes clustering and dimension reduction methods, which have the function of automatic grouping. It extracts essential process information from industrial big data clusters through data mining, identifies information knowledge to promote management decision-making, and executes manufacturing tasks in the simplest operation mode. This process can be explained powerfully. How to make effective safety decisions has always been a hot topic in safety management. Safety-Related Data (SRD) is the most valuable asset of Safety Decision-Making (SDM) [118], which maintains the safety of system components and plays an essential role in promoting the industry's sustainable development. In the traditional mechanical product design process, products have performance requirements and many economic requirements, such as manufacturing costs, operating and sales profits, and considerable uncertainties in many cases [119]. Manufacturing enterprises usually used multi-source heterogeneous real-time data for analysis, such as association analysis, prediction analysis, cluster analysis, and knowledge discovery, etc. [120], which helps decision-makers gain new insights and inspiration.

Early identification of manufacturing defects and timely rework in a complex multi-stage production environment will avoid repetitive maintenance during the subsequent period. An extensible hybrid decision support system (DSS) was developed [121]. It combined the system with applications to visually analyze the characteristic data of manufacturing processes and integrate the ever-increasing data from industrial departments. The rapid growth of information urges enterprises to seek new strategies for the industrial revolution [122]. Model Predictive Control (MPC) is an attractive method in the advanced control of the industrial process, which expresses the system behavior and plans the best control sequence based on the known mathematical model. Still, this method is not representative in practice. Under some unpredictable interference and random noise, data analysis method and machine learning are usually adopted to complement each other, and the prediction model of unknown data is established by fitting historical data, which is convenient to divide the uncertainty into the known part and random error part and construct uncertainty data set. Data-driven decision-making is an emerging paradigm [44]. While big data analytics is reshaping the manufacturing industry, most of the data-driven approaches have not yet been used efficiently in practice. Simple analysis and presentation can't solve all the problems and challenges facing us now or in the future. It is necessary to consider and analyze data-driven models' interpretability as the leading factor in supporting practical industrial applications. An intelligent immune system based on big data was developed [123], and a smart immune mechanism was designed to adapt to the dynamic process and condition changes of the processing system. Real-time monitoring of abnormal manufacturing conditions triggers the rescheduling algorithm, which has carried through a tracking, study and optimisation of the product life cycle process to achieve production optimization and energy efficiency. It accomplished the goal of multi-objective energy-saving output optimisation.

Big data analysis refers to the process of discovering potential value from big data [124]. The increasing data in the industrial manufacturing process indicates that the era of big data has gradually penetrated the industrial field. Sanders et al. [125] applied a lesson-based implementation framework and advanced the supply chain through big data analytics. Big data analysis is particularly essential in a dynamic and competitive market [126]. The spatial scale and functional complexity of the modern industrial production process are increasing rapidly. The production process is often affected by interference and failure, which leads to abnormal events. Therefore, it is necessary to make flexible decisions in real-time to deal with various complex situations in the external environment. The current era of big data has witnessed the broad application of data analysis in the process industry [44], from passive application in process control (process monitoring and transfer sensing) to the active application (optimal control and advanced decision-making). The passive application aims to help people observe and manipulate the process equipment process efficiently. In contrast, the active application tends to act and guide the industrial process through decision-making directly and has a positive impact on its target results. The predictive maintenance process is mainly to obtain the best time for equipment maintenance through simulation [32], thus ensuring the efficient operation of equipment and getting the highest yield benefit in batch production.

3.2. Fault diagnosis and predictive maintenance compensation

Big data analysis has been used to extract sufficient information and obtain efficient intelligent manufacturing. The processing method and formula are selected according to experience, so the efficiency of defect diagnosis and fault detection in product manufacturing is very low. To make up for this gap, Bumblauskas et al. [127] developed two intelligent decision analysis models to predict the failure of specific parts, and created a system that could provide decision support for users and improve product life cycle. The management of essential components in the production system is aimed at handling components with extremely low reliability or with the highest risk, leading to production interruption. A method of identifying essential components and a decision support tool for managing maintenance activities of crucial components in the manufacturing system were proposed [128]. In manufacturing and maintenance, virtual reality improves the operation speed by immersive simulation of the maintenance process and augmented reality provides interactive real-time guidance for operators, which can help monitor product defects without a physical prototype, thus improving the decision-making process and enhancing the information visibility of the process.

In semiconductor manufacturing, Niu et al. [129] developed a yield improvement system, an equipment diagnosis system, a revenue management system, a predictive maintenance simulation system, and applied automatic virtual metering (AVM) to the factory to realize a comprehensive inspection of the workpiece. Big data analysis was used to extract sufficient information and obtain effective intelligent manufacturing. Indeed, the processing method was selected from previous experiences, the efficiency of defect diagnosis and fault detection in product manufacturing was very low. To make up for the gaps, Khakifirooz et al. [130] developed a framework based on Bayesian inference and Gibbs sampling to analyze complex semiconductor manufacturing data for fault detection to enhance intelligent manufacturing. Yan et al. [131] explained the central concept related to devising electrocardiogram(DECG). Then, the regression operation and deep denoising autoencoder algorithm were presented to predict the remaining useful life of industrial equipment. The algorithm workflow and the architecture of the integrated DDA algorithm were provided. The proposed concept and algorithm had great potential to accelerate the development of industrial intelligence.

Advanced data analysis tools can analyze the captured data, prevent predictive failures and effectively reduce downtime caused by unforeseen manufacturing faults. Big data analysis is mainly based on the review of manufacturing events in predictive maintenance, and the prediction of future events. Generally speaking, vibration monitoring is primarily used for system condition maintenance. Still, the effect of predictive maintenance by vibration analysis is not ideal, and the primary purpose of prediction is fault detection. Although there are still many bottlenecks in system detection based on big data, more and more manufacturing companies spare no effort to explore the practicability and applicability of big data technology and related supporting technologies [14]. Through continuous trial and improvement to solve specific problems in actual production, the whole enterprise data value chain is constructed.

The effective manufacturing processes ensure best production outcomes and maintenance activities are taken based on information on the healthy operating status of each system to prevent failures and accidents. A decision support system architecture was proposed to evaluate the running condition of crucial components of the system [41]. It mainly analyzes the pattern of historical and real-time inspection data to help decision-makers implement correct manufacturing system maintenance measures. A big data analysis framework based on state maintenance was proposed [132], which estimated the uncertainty based on backward feature elimination and fuzzy disorder rule induction algorithm to predict error. It also improves prediction accuracy and optimizes the equipment reliability by quantifying the risk of remaining life prediction. The plastic injection molding process is widely used in the Cyclic-Manufacturing Process of plastic parts production, and the quality control of this process is a very arduous task. Kozjek et al. [133] used a holistic approach to predict infrequent faults in cyclic manufacturing, including data generation, acquisition, processing, and prediction.

The manufacturing system is analyzed to maintain the system's high performance and to meet the dynamics and uncertainties of the business environment [134]. Fault diagnosis is usually aimed at distinguishing the types of faults occurring. Mahalanobis distance (MD) has been proved to be a multi-dimensional distance measure. The usual data dimension reduction method is to map the high-dimensional space to the low-dimensional space when the dimension of the original data is plentiful, but the processing result is not accurate due to a large number of noise and redundant factors. A generalized distance measure was proposed in conjunction with a novel hierarchical dimension reduction approach [110]. All fault data points were separated from health data points, and fault data points were classified into corresponding fault categories. This method could improve the performance in high-dimensional scenes of standard classification methods.

The basic algorithm framework for fault detection and diagnosis is mainly divided into three parts:

- Separate normal and abnormal data, accurately classify and mark them.
- Perform fault defect detection based on the algorithm training model.
- Analyze the results and feedback to guide decision-making and assist in solving related problems.

The traditional "knowledge modeling" paradigm has been questioned in industry, Rousseaux et al. [135] proposed big data and data-driven intelligent predictive algorithms supported creativity in industrial engineering, aiming to choose useful knowledge spatiotemporal disposition. Based on this innovation, relative configuration and accuracy become the two main parameters of knowledge improvement.

3.3. Green manufacturing and energy awareness decision-making

The United Nations Environment Programme defines clean production as a comprehensive preventive environmental strategy that is continuously adapted in production, processes, and services. Clean Production (CP) is a crucial means for manufacturing companies to achieve sustainable production and enhance their sustainable competitive advantage, aiming at improving production efficiency, environmental management, and human development. The primary task in the manufacturing sector is to reduce the emissions of production waste at the source rather than makeup for the salvage losses after the end of the production process. However, CP has many obstacles in the actual strategy implementation and faces enormous challenges in the coordination and optimization of decision-making in the whole implementation process. A framework of product life cycle analysis based on big data was proposed [120], which focused on the manufacturing and maintenance process of the product life cycle, and found out valuable information such as association and hidden patterns from product life cycle data, thus promoting the implementation of cleaner production (CP).

Energy and environmental problems have aroused the concern of manufacturing enterprises on energy conservation and emission reduction [136]. To reduce the energy consumption and emission in energy-intensive production sectors, Zhang et al. [137] proposed a big data-driven analytical framework to reduce the energy consumption and emission. Big data acquisition and mining, these two key technologies are used to analyze big data energy. The proposed framework was demonstrated in an application scenario of ball mills in the pulp workshop. Experiments showed that energy costs and energy consumption were reduced by 4% and 3%, respectively. These improved methods could promote the sustainable development of the energy-intensive manufacturing industry.

The popularity of big data technology has changed the traditional business model design and business decision, which helps manufacturers to make accurate decisions, reduce the randomness and fuzziness of reverse logistics, and improve the operational efficiency and service performance of recycling equipment products [138]. The manufacturing process will cause a lot of energy consumption. In recent years, incentive measures related to energy efficiency have come into effect, promoting the overall transformation of manufacturing towards sustainable development. A conceptual framework of big data analysis was proposed to analyze the impact of big data on manufacturing redistribution, create common value, and make the manufacturing value chain more inclusive [24]. In recent years, more and more manufacturers have brought remanufacturing into the manufacturing system to form a closed-loop manufacturing system [138]. Considering the economic benefits of recycling, remanufacturing has become an urgent strategic measure for enterprises. A cyber-physical system based on big data-driven machining process optimization was proposed [139], and a new energy model was developed to support the energy efficiency optimization in the whole manufacturing life cycle, taking full account of the dynamic failure and corresponding adjustment requirements of the machine tool system in the manufacturing life cycle. Redistributed manufacturing refers to the manufacturing business model, strategy, system, and technology that changes the manufacturing industry's economy and organization, which is closely related to the manufacturing environment and scale [140]. Green manufacturing pays attention to high-level efficiency and safety, reflecting stricter environmental policies and more efficient fault prediction and maintenance [141]. Industrial big data analysis is an essential strategic theme of manufacturing development. This paper discussed the synergistic effect of industrial big data in data collection and infrastructure [142]. An embedded method based on meta-heuristic and principal component analysis was proposed in the cellular manufacturing system [143]. It used large-scale data to solve the problem of sustainable, robust random cellular equipment layout.

The concept of green manufacture has become increasingly popular with global warming. In the era of big data, advanced technology can collect a large amount of demand data for analysis and promote the development of intelligent industry [144]. However, the economic growth model of high pollution and high energy consumption has seriously threatened the environment, and manufacturers have gradually introduced smart technologies to support the sustainable development of the industry. To realize green manufacturing, remanufacturing has become an efficient form of resource recycling. Still, the remanufacturing field is highly uncertain, and it isn't easy to meet the requirements of the optimal decision [145]. The booming data age has dramatically affected the process industry. Efforts must be made to improve energy production, rationally implement energy distribution, and reduce energy consumption to achieve intelligent manufacturing [143]. The potential dynamics, predictability, adaptability, flexibility, and scalability of industrial big data are the critical features of data-driven methods. The big data generated during the operation of the manufacturing execution system was used to support operational management decision-making [146], learning from historical behavior patterns and predicting possible bottlenecks in the future manufacturing process will help the decision-making process.

4. Challenges of industrial big data in intelligent manufacturing

The manufacturing industry is transforming the technological paradigm [147]. Nowadays, big data-driven analysis is still in the initial stage of the Industrial Internet of Things, and further efforts need to be made to meet the needs of its industry and market to transform traditional manufacturing engineering into data engineering. The research on the effects of big data analysis on manufacturing decision-making is a hot topic and emerging field today. Still, the development of industrial big data-driven technology is also facing many severe challenges driven by the times. The challenges facing industrial big data technology at this stage are as follows:

- The problem of data quality management: High-quality big data plays an essential role in intelligent manufacturing. The scale of the data set is beyond the acceptable range of common software tools, resulting in poor data processing ability. A large number of useful data are hardly utilized to help leaders and decision-makers make accurate decisions, resulting in a waste of resources.
- The problem of data security and privacy protection: To be competitive in the global manufacturing market, enterprises must ensure the safety and reliability of data. The development and application of big data analysis tools require a lot of investment and extra work, which may consume a lot of resources and financial resources. The existing technology of big data management is costly. At present, most existing technologies can't meet the current infrastructure requirements, and there is no strategy to share data among organizations. Various types of data from different sources may lead to the complexity of data integration. While providing sufficient information to users through data mining, there is a severe threat to the privacy and security of data information.
- The problem of the generality of the conceptual framework in actual production: The solution cannot describe a practical method for presenting analysis results and actual conditions in the real manufacturing environment, and cannot provide complete and correct information for end-users and decision-makers. Most conceptual frameworks and analysis methods are only useful for a specific type of industrial manufacturing, but not universal in industrial production. They do not adequately describe the data analysis process methods in detail and do not grasp the critical elements needed to develop specific data analysis schemes.
- The problem of data integration processing in industrial manufacturing systems: Industrial big data is noisy and redundant, and if a large amount of valuable data is lost, the loss of enterprises is too significant, and the data quality is of considerable significance to the value of many enterprises. The data volume is enormous and diverse, traditional single-processed data analysis can't quickly integrate to obtain heterogeneous data knowledge and the target value, because of the various varied characteristics, security and other reasons of the data itself, manufacturing industry for the integration of industrial big data processing is very difficult.
- The problem of accessing primary manufacturing data: the data accessibility of the whole manufacturing network supports massive data to specify the performance required for strategic decision-making. When faced with incomplete or invalid data, it isn't easy to extract and convert primary manufacturing data. The data analysis platform can't directly use direct data in the manufacturing system for processing and analysis. It needs to open the data access function, export its sample data for storage and then enter the preprocessing stage.

5. Investigated method

This paper proposes a conceptual framework of intelligent decision-making analysis based on industrial big data-driven technology, and also introduces the functions and core design ideas of each part of this framework. It combines industrial big data, CPS, digital twin and other technologies (as shown in Fig. 4). In this study, a shared data-driven model is presented to deal with big data of industrial production. This model covers the process of data

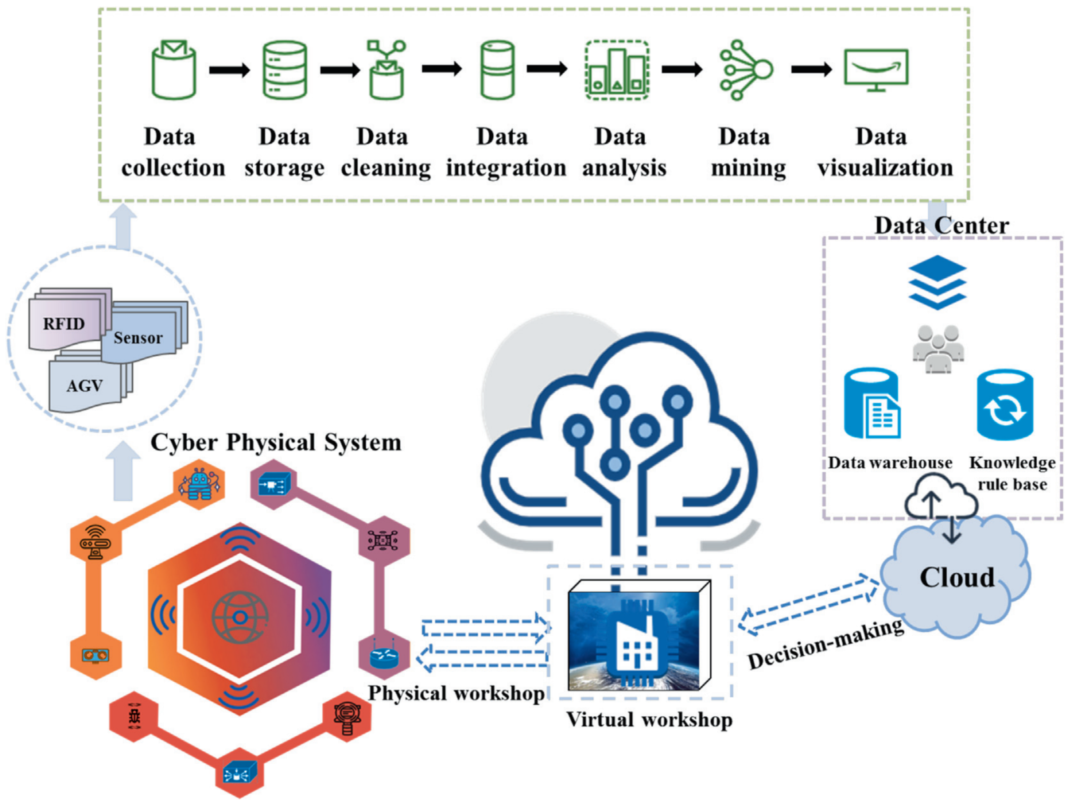

Fig. 4. The conceptual framework of intelligent decision-making analysis based on industrial big data-driven technology.

collection, storage, cleaning, integration, analysis, mining and visualization. This method develops a brand-new intelligent manufacturing paradigm, which focuses on real-time dynamic perception and accurate decision-making based on big data-driven analysis in manufacturing environment. It pays attention to the interactivity and standardization of data, and promotes the speed of data exchange between data providers and data users through distributed data processing.

The main working mechanism of the conceptual framework of intelligent decision-making analysis based on industrial big data-driven technology is as follows:

- The working mechanism of industrial big data analysis: In a complex manufacturing environment, industrial production data is captured by many sensors in the production physical system, and then the whole process of data collection, storage, cleaning, integration, analysis, mining and visualization is carried out. Finally, the Data Analytics Center collects industrial big data, stores it, and generates relevant knowledge rule base, and then upload these data rules and analyzed features to the cloud for sharing. The operating system based on big data technology collects and transmits sensor data distributed on devices. The system has a high degree of transparency, which aims to summarize, correlate, process and analyze data information, and integrate and understand the characteristics of data information. In addition, the analyzed data information features can be integrated and understood to control the causes of corresponding manufacturing events, presenting cognitive information to leaders in the right way to help them make decisions.
- The working mechanism of intelligent decision-making analysis in industrial manufacturing: The decision-making process in industrial manufacturing begins with building a large database of decisions. The industrial decision database consists of input data for decision tasks, including bill of materials data, demand list data, production planning data, manufacturing job management data, and so on. Expanding decision databases and verification standards on industrial big data systems will improve the precision of manufacturing decision-making tactics, thereby enhancing the potential competitive advantage of manufacturing enterprises. Decision data is the basis for strategic deployment of manufacturing enterprises. The main criterion of decision-making is the matching degree of ability and resources. Industrial big data-driven manufacturing systems are deeply integrated and interact to guide industrial manufacturing control systems to react in a short time or in real time for rapid decision-making. Intelligent decision analysis based on industrial big data is the process of feedback and coordination from the virtual world to the physical world, which aims to strengthen the intelligent function of manufacturing systems, so that manufacturing systems can adapt to the environment and operate sustainably in continuous practice, adjustment and collaboration.
- The working mechanism of virtual simulation technology: Dynamic scheduling and optimization in digital simulation environment ensures that energy consumption remains within the ideal controllable range. In the intelligent manufacturing system, firstly, the relevant production parameters are defined to make a reasonable production plan, and then the simulation and optimization are effectively coupled. Simulation optimization is solved by digital twin, which can be regarded as virtual copies of physical products, reflecting the real-time situation of physical operation, and implementing simulation operations in virtual replicas to trigger new inspiration. To improve the scalability of the simulation model, the security and interoperability of the data stream needs to be ensured, especially time-related data (such as device configuration, human–machine col-

laboration, transportation routes, etc.). The autonomous component modules are embedded to improve the adaptability of the manufacturing system.
- The complementary working mechanism of the framework: Manage industrial manufacturing data reasonably to ensure the quality of industrial big data. The workflow is processed automatically to ensure the autonomy of the whole intelligent system, and the proprietary modules are maintained regularly.

The design principles of this intelligent decision analysis framework for industrial big data-driven technology are as follows:

- Ensure real-time transmission of industrial manufacturing data: The value chain of the entire manufacturing system includes suppliers, materials, logistics, etc., and the relevant participants coordinate and cooperate according to their own needs to form a dynamic ecosystem. This system must provide real-time responses to all stakeholders to ensure that interactive feedback for services and real-time decisions is available.
- Ensure the integrity and security of digital manufacturing data: Sensor devices in distributed networks monitor the real-time status of intelligent objects and process information data. Big data analysis can coordinate the collaboration of intelligent objects and feed them back to self-organization networks in real time. The strong anti-interference ability of this system ensures the integrity and security of data.
- Ensure interoperability between different technologies: The intelligent decision analysis framework based on industrial big data integrates many technologies such as CPS, big data, cloud, and digital twin, etc. This framework takes into account virtualization technologies at all levels of the system. Big data analysis can dynamically perceive and track product manufacturing process, predict market demand, and ensure the reconstruction and optimization of manufacturing process.

6. Conclusions and future research

In this article, we provide an overview of industrial big data for intelligent decision-making, then introduce the application of big data-driven technology in intelligent manufacturing, and explain the existing problems and challenges in this field. In order to solve these problems,we present an intelligent decision-making analysis framework based on industrial big data-driven technology, and introduce the function and core design ideas of each part of this framework. This approach develops a new intelligent manufacturing paradigm that focuses on dynamic perception and accurate decision-making based on big data-driven analytics in manufacturing environments. This paper introduces big data-driven technology into the field of intelligent decision-making in manufacturing, aiming to add new vitality to traditional manufacturing systems and lay the foundation for sustainable manufacturing in the future.

The main limitation of this study is related to the distance between the two fields of research involved. Firsts, reliability is a topic strongly linked to the exact sciences, such as engineering and mathematics. Second, Big data, on the other hand, has its bases deeply centered on information technology. In the actual manufacturing activities, the absorptive capacity of data information, information knowledge leakage, interference and other factors will have an indirect impact on the production decision-making. This conceptual framework of the new paradigm introduces industrial big data driven analysis into manufacturing system. However, this hypothetical model of big data analysis is built in an ideal environment, the reliability and practicability of this conceptual framework need to be further verified.

This research will further develop the framework and explore in depth, including the development of software systems and the implementation in industrial manufacturing. In addition, this manufacturing system will further help develop, implement and operate manufacturing solutions through big data analysis. At this stage, studying the impact of big data analysis on manufacturing decision-making is a hot and emerging field. We hope this systematic review will be useful for researchers who want to study the field of industrial big data.

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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