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Blockchain Network Based Topic Mining Process for Cognitive Manufacturing

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Abstract

Cognitive manufacturing has brought about an innovative change to the 4th industrial revolution based technology in combination with blockchain distributed ledger, which guarantees reliability, safety, and security, and mining-based intelligence information technology. In addition, artificial intelligence, machine learning, and deep learning technologies are combined in processes for logistics, equipment, distribution, manufacturing, and quality management, so that an optimized intelligent manufacturing system is developed. This study proposes a topic mining process in blockchain-network-based cognitive manufacturing. The proposed method exploits the highly universal Fourier transform algorithm in order to analyze the context information of equipment and human body motion based on a variety of sensor input information in the cognitive manufacturing process. An accelerometer is used to analyze the movement of a worker in the manufacturing process and to measure the state energy of work, movement, rest, and others. Time is split in a certain unit and then a frequency domain is analyzed in real time. For the vulnerable security of smart devices, a side-chain-based distributed consensus blockchain network is utilized. If an event occurs, it is processed according to rules and the blocking of a transaction is saved in a distributed database. In the blockchain network, latent Dirichlet allocation (LDA) based topic encapsulation is used for the mining process. The improved blockchain distributed ledger is applied to the manufacturing process to distribute the ledger of information in a peer-to-peer blockchain network in order to jointly record and manage the information. Further, topic encapsulation, a formatted statistical inference method to analyze a semantic environment, is designed. Through data mining, the time-series-based sequential pattern continuously appearing in the manufacturing process and the correlations between items in the process are found. In the cognitive manufacturing, an equalization-based LDA method is used for associate-clustering the items with high frequency. In the blockchain network, a meaningful item in the manufacturing step is extracted as a representative topic. In a cognitive manufacturing process, through data mining, potential information is extracted and hidden rules are found. Accordingly, in the cognitive manufacturing process, the mining process makes decision-making possible, especially advanced decision-making, such as potential risk, quality prediction, trend prediction, production monitoring, fault diagnosis, and data distortion.

Extended author information available on the last page of the article

Keywords Cognitive manufacturing · Distributed ledger · Topic mining · Blockchain network

1 Introduction

Cognitive manufacturing exploits the convergence of intelligent information technology and manufacturing technology to apply the standardized industrial engineering SW, ranging from production to distribution, to all aspects of society. To keep sustainable productivity, innovative intelligent information convergence manufacturing is promoted as one growth engine area. The manufacturing industry innovatively changes owing to the convergence of intelligent information, pattern recognition, data mining, machine learning, big data, Internet of Things, and manufacturing technology, in preparation of the 4th industrial revolution [1–4]. Next-generation convergence technology and intelligent information systems are expected to significantly improve conventional manufacturing systems. There has been research on the advancement of the intelligent manufacturing systems optimized with the combination of intelligent information technology, not only in logistics processes including production, logistics, distribution, and consumption, but also in facility processes and quality control processes. For the efficient development of the system, it is necessary to conduct manufacturing big-data-based data mining analysis and the design and analysis of an intelligent system to prepare manufacturing security and blockchain network, manufacturing service technology, and other base technologies [5]. Population ageing and population decreases lead to changes in the production system, and the mining process for decision-making in manufacturing big data exploits the collection and pre-processing technology of heterogeneous big data, big data distributed storage and management technology, and big data analysis technology [6, 7]. To process the unstructured manufacturing data as process structured data, distributed-process-based integration is performed. It is necessary to research the advancement of the convergence technology to effectively process the collected unstructured big data. In addition, there is research on the sharing and security of the distributed ledger of work process transaction in the application of the blockchain technology used in the financial area to manufacturing and associated processes. In the IoT network, cognitive manufacturing exploits the blockchain to make possible transparent, scalable, and safe processes, and changes from a centralized type to a distributed type. The blockchain is classified into public blockchain, hybrid blockchain, consortium blockchain, and private blockchain. These blockchain technologies are applied to energy, logistics, distribution, finance, medical science, automobiles, and public services. In order to share a transaction database in blockchain and side chain structures, an integrated type is provided in a platform. IBM developed a project that established a large platform where a variety of blockchain platforms are connected and integrated with each other [8]. This integrated blockchain platform can connect the blocks of trade transactions, establish them in a distributed type, and share transactions by block. The mining process using trade transactions that occur in real time makes it possible to analyze big data, draw meaningful rules, and conduct a reasonable decision. In a cognitive manufacturing, data mining is applied to draw meaningful rules that are applied to the manufacturing process. This technology is capable of saving cost effectively and improving productivity and quality control in a cognitive manufacturing. The distribution manufacturing process includes product carry-out, warehouse carry-in, warehouse load, warehouse carry-out, wholesale carry-in, wholesale carry-out, and organization carry-in. Trade transaction is comprised of manufacturing production, production carry-out, wholesale carry-in, and wholesale carry-out in terms of information flow. In a cognitive process, it is possible to shorten the production times and distribution and establish an optimization plan, and save time and cost through reassignment of inefficient processes. In product manufacturing and distribution, it is possible to reduce inventory volume and thereby save cost, lower a product price, and increase sales. Accordingly, consumer satisfaction and market sharing improve.

This study is organized as follows: Sect. 2 describes the related research and Sect. 3 describes the blockchain network based topic mining process for a cognitive manufacturing. Section 4 describes the experimental result, and Sect. 5 provides a conclusion.

2 Related Research

2.1 Recent Issues of Cognitive Factory

The production system known as factory automation is aimed at minimizing human resources and making a process unit efficient. Therefore, it is based on high functionality and precise processing capability of an automated machine, and focuses on increased productivity and quality. In a more comprehensive concept, it exploits business management models like ERP, CRM, and decision-making in order to integrate and systemize information. These models make it possible to predict demands and efficiently and immediately respond to production and supply plans. However, the system is based on a bottom-up information delivery system and generates a different cycle of responses depending on demands. Accordingly, it has a limitation in meeting the rapidly changing demands of small quality batch production. To overcome this problem, the pull-type-based Toyota Production System (TPS) aimed at zero-inventory, zero-defect, and flexible production was developed. In the national dimension, Germany established Industry 4.0 for cooperation between the government, companies, and academic circles. In Japan, the Industrial Value Chain Initiative (IVI) consultative group was established based on companies. In the US, based on GE, ICT enterprises have cooperation. As such, cognitive manufacturing develops into government or company research. In terms of implementation, cognitive manufacturing is based on industrial robot technology, and requires multiple equipment controllers and IoT technology that supports data collection. In addition, to analyze and process the collected data, Hadoop and others are used. Based on the statistical analysis of pre-processed data, more enhanced AI analysis methodology can be applied to the control and development of the production process line. AI with an improved learning ability will help to operate stable equipment for cognitive manufacturing and thereby will greatly improve the quality and productivity of products. Figure 1 shows the cognitive manufacturing infrastructure information processing procedure.

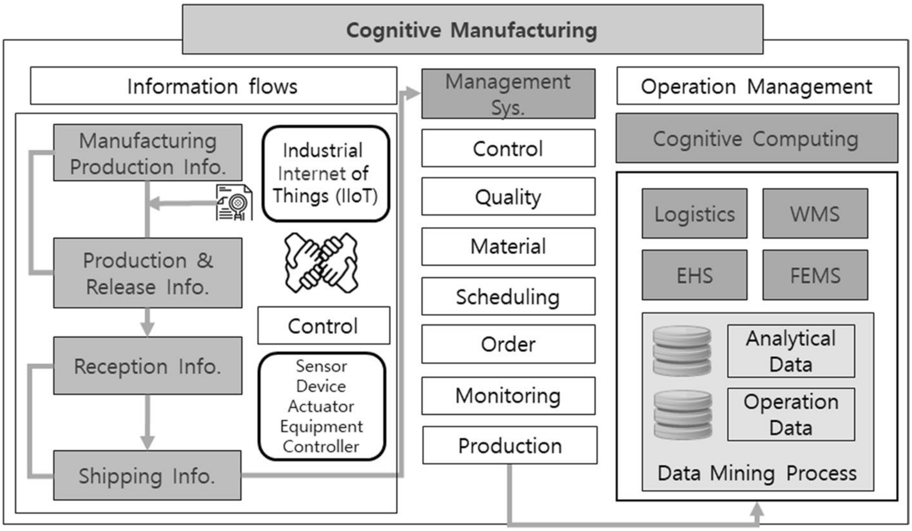

Fig. 1 Cognitive manufacturing infrastructure information processing procedure

2.2 Blockchain for Cognitive Computing

With the development of convergence technology and changes in consumption trends, industries are increasingly focusing on personalized production. As a result of personalized production, product purchasing involves considerations of raw materials, country of origin, date of manufacture, and distribution channel. With the propagation of the internet, consumers can easily collect information on products and their needs have become more diverse. Consequently, the product life and release cycle of new products are becoming shorter, and consumer expectations are becoming higher [9]. The manufacturing industry is transforming itself away from the existing mass customized production toward the personalized production that utilizes demand analysis and trend forecast. Personalized production aims to create new service values and provide differentiated services through the cooperation of different industries. It is also characterized by high quality, low cost, product diversity, and service utility, and offers a wide choice of products for consumers. Increasing attention is given to the cognitive process that applies convergence technology to mining technology for personalized production [10]. Various technologies, such as IoT, cloud computing, AI, big data, and data mining are required according to the phase through the whole process from planning to sales in the cognitive process [9]. The cognitive process is structured in connection with all objects related to manufacturing in different areas, such as health, raw materials, energy, components, machine, and medical care. It also requires an environment where cooperative work is made possible through various connections: human to object, object to machine, machine to human, and industry to industry connections [11]. This helps maximize the flexibility of the process and makes it possible to cope with changes in a manufacturing process, market demand, and the like. A cognitive process produces different analysis results depending on collected data. It requires collaboration through a large network and transparent and reliable data to do so. The blockchain-based cognitive manufacturing process records the data with integrity through a distributed ledger and a distributed consensus of the blockchain. In an effort to take the lead in the fourth industrial revolution, international standardization institutes are established around the world and development activities to establish international standards are being carried out [9]. With the development of convergence technology, consumers use an increasing amount of information when selecting goods, and their expectations are increasing. A mining process based on distributed consensus and distributed ledgers is also developed. The process is a way to prevent errors or fabrications that may occur in the process of planning, designing, production, distribution and sales by applying distributed ledgers. A distributed ledger is one of the essential concepts of blockchain, as well as a record of consensus among participants [12]. This is a method to manage product histories by applying blockchain-distributed ledgers and a blockchain-distributed consensus to the mining business process. A distributed consensus is a way to derive the consensus regarding specific data among participants for a higher reliability. In cognitive manufacturing, a distributed ledger displays the characteristics of sequence data, with continuous data in time sequence according to the condition of products. The condition of products continues to change according to the manufacturing process and products are made into blocks to be recorded in a distributed ledger. For example, the distributed ledgers may provide data about products to which similar raw materials or manufacturing processes are applied, through association analysis of mining and data visualization. Distributed ledgers provided to consumers should utilize association mining analysis and data visualization so as to help them to utilize in actual purchasing. Moreover, the mining business process suggested in cognitive manufacturing can be applied to increase the reliability and flexibility of the ledgers. This allows the provision of transparent information to consumers as well as increase in the reliability of the mining business process.

3 Blockchain Network Based Topic Mining Process for Cognitive Manufacturing

3.1 Manufacturing Process Monitoring and Feature Extraction

In the past, the equipment, human resources, or user dynamic context management, which were managed in factories or offices, were of the bottom-up type and based on statistics, and particular detection equipment was limited to the analysis on production errors, or the movement path and time of human resources. Accordingly, such equipment was used mostly for fault diagnosis or to control human resources, and was negatively evaluated by the human resources to be controlled. At present, with the spread of smart devices, it is possible to obtain a variety of sensor information from users, and to deeply analyze process monitoring, error prediction, and dynamic situations of human resources. Accordingly, based on the management of dynamic situations, it is possible to predict a production line failure, extract health information on production human resources, and provide personalized health service [4]. In particular, the health service for human resources can contribute to improving welfare, work conditions, and production efficiency [13, 14].

Detection sensors for manufacturing process monitoring and health care service vary and have a wide range of attachment. Typical ones include sound and accelerometer sensors attached to production equipment. If such a sensor is used to analyze a vibration waveform, a constant and repeated pattern of waves is observed. Accordingly, it is possible to catch equipment malfunctions based on a waveform change, and to predict some errors of large connecting production equipment to select maintenance objects and optimize operation. Likewise, accelerometer sensors attached to human resources make it possible to find their movements and model the classification of work situations and the detection of safety situations [15]. In order to respond to a variety of sensor input information, this study exploits the highly universal Fourier transform, which is capable of analyzing the situations of equipment and human body motions. As a sensor, the typical universal sensor "accelerometer sensor" is applied. An accelerometer sensor is able to measure acceleration energy of a moving object. The measured structured data is applied to find and analyze the movement pattern and posture of a user. In addition, dynamic energy released during exercise, rest, and movements can be measured. The Fourier transform algorithm used for pre-processing has input signals that fluctuate as a function of time elapsed. Therefore, it is easy to analyze a specific form of frequency and it is possible to detect a movement change depending on the input of a sensor. Fast Fourier transform (FAT) generally used for frequency analysis is unable to analyze associations in time [16, 17]. Accordingly, for frequency analysis, it is necessary to use short-time Fourier transform in a real implementation. The transformed short-time Fourier transform divides time in a certain unit to analyze the frequency domain. On balance, it is possible to conduct a limited analysis on frequency in time. The short-time Fourier transform is written as in the Eq. (1).

$$\mathrm{G(f)} = \int_{ST}^{ET} F(t)e^{-i2\pi ft}dt \tag{1}$$

In the Eq. (1), *ST* means a start time in the time division, and *ET* is an end time; *t* means a time; *f* represents a frequency; *i* means an imaginary number. The frequency generated in pre-processed production equipment can vary, but the transformed graph confirmed in time has a constant form. Accordingly, it is possible to compare the size saved as the discrete value of each frequency at the initial normal operation and the waveform of the current equipment in operation. The error value *E* is written as in Eq. (2). When the frequency section separated by *Fourier transform* is divided by *n*, *i* means each frequency section, and *Ni* is the first normal value entered at the normal operation of *i* section. S_i means the frequency of *i* section of the current input.

$$E = \sqrt{\frac{\sum_{i=1}^{n} \left| N_i = S_i \right|}{n}} \tag{2}$$

Therefore, it is necessary to obtain the measured normal value that is used for real fault diagnosis. The larger the real-time measured *E* value is, the higher the probability of observing an abnormal state is. On the assumption that the allowable size is *G*, lowering the *G* value comes closer to the maintenance concept based on prediction. A person in a working level needs to adjust the *G* to endure actual maintenance work frequency. In the meantime, production human resources have various motions and movements, and it is necessary to classify frequency with section *n*. The *E* value is used as an evaluation indication of similarity. The frequency input by unit time is compared with its past value in order to group by similarity. Accordingly, it is possible to make a variety of classifications, such as fixed posture, horizontal movement, stair move, and fast movement. The collected sensor data should be set to industrial confidentiality, and life log data should be treated especially carefully as personal information. In this aspect, information protection and safety in data transmission are of significance. The blockchain has a type of distributed storage so that it is difficult to make forgeries and falsifications. Because of its excellent safety, the blockchain becomes a critical factor in a cognitive manufacturing processes.

3.2 Blockchain Network in Smart Devices

Smart devices include IoT devices, wearable devices, ambient sensors, drones, CCTVs, home appliances, health devices, and medical devices, and the devices to control them. They are attached to the human body directly, or installed in main posts in order to collect data on humans and the surroundings. The data collected by smart devices directly influences the safety and security of industrial sites or factories, so that they need to be analyzed quickly and accurately. Smart devices can easily be connected via Wi-Fi, Bluetooth, and LTE. For this reason, they have weak security. To minimize the missing values of the collected data, it is necessary to continue to maintain smart devices. For the weak security of smart devices, a blockchain-technology-based network is established. Blockchain is classified into public blockchain, hybrid blockchain, consortium blockchain, and private blockchain. Public blockchain is the fully opened blockchain in which large users like virtual coin users participate in distributed ledger and distributed consensus. Consortium blockchain is the blockchain where consortium members participate in distributed ledger and distributed consensus. It features the identification of users. Private blockchain is the blockchain where small allowed users can participate in distributed ledger and distributed consensus. Smart devices include activity information of enterprises and individuals so that they use consortium blockchain where participants are the main body of management. Therefore, only allowed users can access data [9, 12].

Smart devices continue to generate and collect massive amounts of data. Because of the structural problem of the blockchain, it is difficult to include massive data. To overcome the structural problems, a side-chain-based blockchain is used. Side chain exploits the advantage of a conventional blockchain which is impossible to manipulate. So as to create the data storage space in the blockchain [5, 18]. In the proposed method, the data of smart devices is saved in a separate database, and data mapping occurs in the transaction of side chain in block. As a result, it is possible to search for data quickly. Figure 2 illustrates the side-chain-based data block in a smart device. In the figure, workers as client and managers for distributed consensus participate in a consortium. A data block includes a creation date, hash information of its connected block, and side chain information. In a data block, side chain has a set of multiple transactions. A transaction set includes smart device information of a worker, mapping information of collected data, event and its process information, and the number of participants in distributed consensus.

The members of a consortium take part in distributed consensus for creating a new block. A consortium has human resources related to production, and a distributed consensus is achieved through the agreement of a majority of consortium participants. A distributed consensus for creating a new block occurs when an event occurs or in the unit of a worker schedule. If an event occurs, it is treated according to event rules. A new block is created through distributed consensus and is linked to the blockchain. Unless an event occurs until a worker finishes its schedule, a new block is created at the end point through distributed consensus and then is linked to blockchain. Created blockchain and smart device data are saved into a physically distributed storage in a type of distributed ledger in order for consistency and data management. Figure 3 presents the creation and management of a new block in consortium blockchain. In the figure, if an event occurs, it is treated according to rules; the data created until the event occurs are integrated and then a data block is created. The created data block is saved into distributed database through distributed consensus.

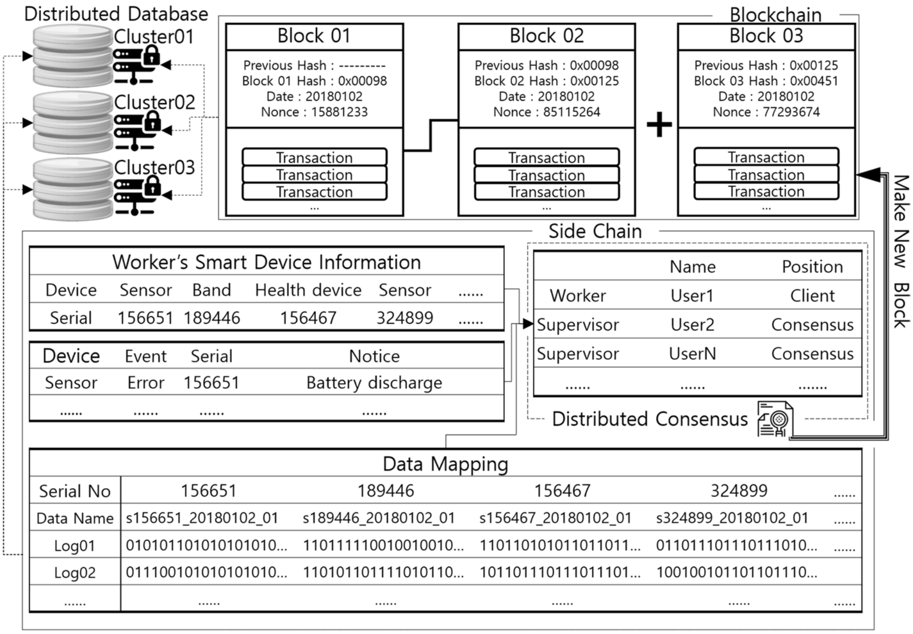

Fig. 2 Side chain-based data block in a smart device

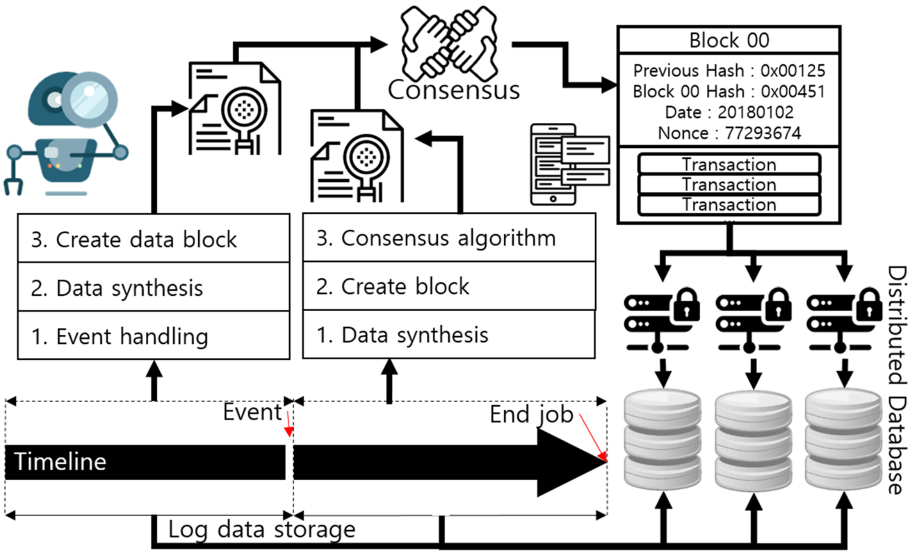

Fig. 3 Creation and management of a new block in consortium blockchain

4 Experimental Results

4.1 Blockchain Distributed Ledger in Cognitive Manufacturing

Facility maintenance, work, worker safety, worker health, product failure, manufacturing time, and others arising in cognitive manufacturing process are analyzed through data mining. In a blockchain network, the block created with the consensus of the worker, equipment manager, work manager, and other employees related to manufacturing is used [4, 18, 19]. A block means a bundle of the transactions transmitted during a particular time, and consists of a block header and block body. In case the data is transmitted in the blockchain, its privacy is guaranteed through the anonymity of the sender and receiver. In a cognitive manufacturing process, blocked transactions and data mining are applied to extract meaningful information. The blocks selected by consensus algorithm are linked with each other to create a blockchain. Each block has two kinds of hash information. One is the hash information of the header of the previous block, and the other is the hash information of transaction. For the ledger of transaction information in cognitive manufacturing, the distributed ledger technology to jointly record and manage it through peer-to-peer based network distribution is applied [14, 15, 20]. Figure 4 illustrates blockchain-distributed ledger-based cognitive manufacturing. In a blockchain network, a cognitive manufacturing process determines a data reading point, P2P-based data transmission or processing, and other details [4, 7, 21]. Because of its primitive management, an cognitive manufacturing process can have problems including the absence of efficient statistical information, negligence of supervision, and inconsistency of physical and soft data. The conventional physical cognitive manufacturing system has unclear information in the manufacturing process, whereas the proposed cognitive manufacturing process supports End-to-End trace based on the transaction data saved in multiple blockchains in order to prevent data loss in each step. The blockchain-based cognitive manufacturing process exploits the information exchange of the data collected in real time so as to analyze a variety of data related to traceability system, extension infrastructure in each base, and worker's work system. Therefore, the

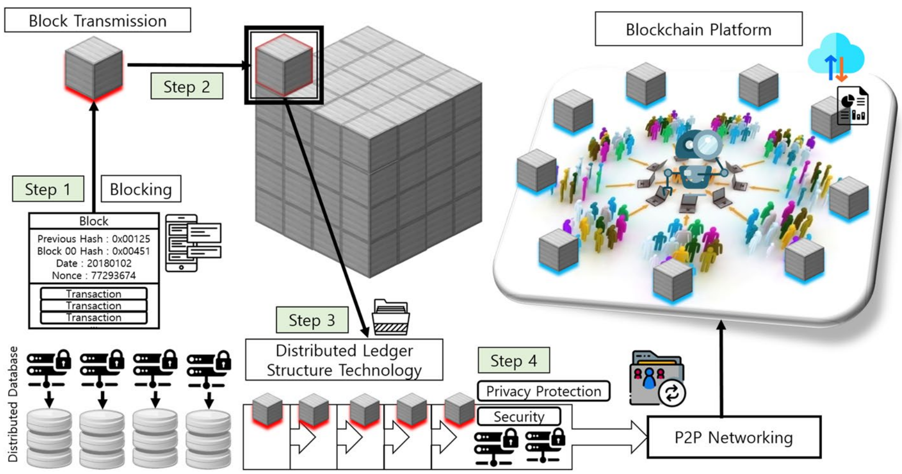

Fig. 4 Blockchain-distributed ledger based cognitive manufacturing

blockchain-distributed ledger-based mining technology provides innovative service in a cognitive manufacturing process.

4.2 Performance Evaluation

Data mining is the process of analyzing and exploring data in order to find meaningful rules and relations from unstructured or structured data. General data mining performs expression search of manufacturing process in order to analyze data meaning. However, the analysis results are not enough to analyze meanings in a data collection step. In particular, it causes the problem of meaning analysis in order to analyze the data of limited views with the use of the transaction of the blockchain network type proposed in cognitive manufacturing process. Accordingly, through topic encapsulation of transaction, meaningless data variables are removed and the primary variables are extracted. Topic encapsulation is the formatted statistical inference method of analyzing a semantic environment from data [22]. The topic encapsulation method is able to find a potential topic of data when blockchain transaction data is applied [23, 24]. Figure 5 illustrates the topic encapsulation process of a blockchain transaction. The topic encapsulation process consists of six steps [22], each of which presents a different data set of each manufacturing stage in a blockchain transaction. Steps 1–3 shows the filtering process of original blockchain transaction for topic encapsulation with the use of transaction data. Step 4 presents the pre-process for removing duplicate manufacturing stages, extracting stems, and creating the {manufacturing stage, item} matrix, where item means the data of transaction that can occur in cognitive manufacturing process. This means all words and sentences appearing in manufacturing process, such as worker, equipment, product information, process step, and process content. Step 5 shows the data process in the {manufacturing stage, item} matrix for topic encapsulation. Lastly, step 6 presents a data set as the result of topic encapsulation.

In a semantic environment, a web robot agent [25] is used to collect data through extraction, conversion, and load, and to give a meaning to the transaction in each step. In the data conversion stage, extracted data is refined, converted, integrated, and summarized. To calculate the similarity of items, the relation between potential variables of each item is judged. Bag of Words [26] identifies the distribution of items appearing in each step and

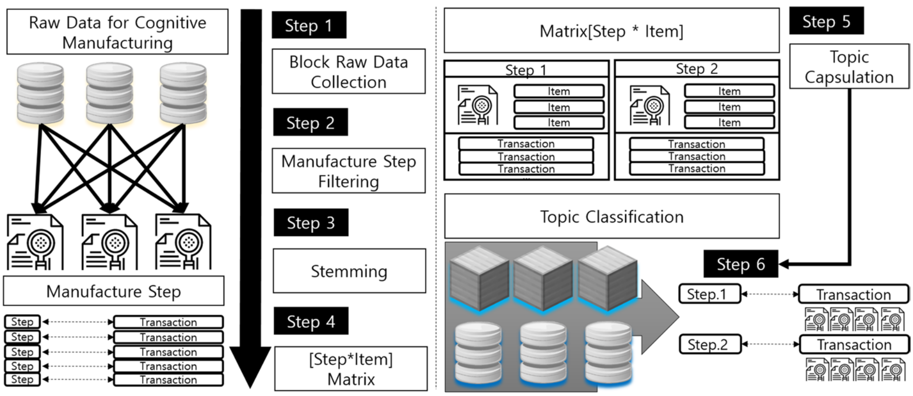

Fig. 5 Topic encapsulation process of blockchain transaction

classifies a manufacturing stage automatically. Through semantic analysis, the frequency of items in each manufacturing stage is expressed, representing the {manufacturing stage, item} matrix. In order to apply the sequential pattern continuously appearing in a manufacturing stage, and the associated rules of items appearing at the same time in the stage, data mining is used. In addition, a random variable of the α (alpha), β (beta) value is used to apply Smoothing based LDA [22, 27].

In the case of LDA-based topic encapsulation, even if the same data and same parameter value are applied, a difference can occur in encapsulation. Accordingly, in order for reliability of encapsulation results, it is necessary to execute modeling repeatedly and designate the topic judged to bring about a meaningful result as a category topic. The items frequently appearing in one manufacturing process should be clustered, and it is necessary to exclude a situation where most items are determined to be a representative topic. The more the items allocated to a topic are independent, the weaker the unity is, whereas the less the allocated items are, the stronger the unity is. Therefore, related items have topic encapsulation. In a cognitive manufacturing process, it is possible to classify risk factors through topic mining process. A risk has four levels: safety, attention, warning, and danger.

For performance evaluation, the accuracy of the proposed blockchain based topic mining process is compared with that of the blockchain based manufacturing process. As the basic data, 10,000 transactions based on a variety of variables offered by a cognitive manufacturing platform [5, 22, 14, 28]. With the collected transaction, the performance of a predicted result is evaluated by Blockchain based Manufacturing Process (BbMP) and Blockchain based Topic Mining Process (BbTMP). The table shows the results of precision, recall, and f-measure, respectively, when the number of transaction is increased. Table 1 shows the levels of accuracy of the F-measure analysis results of applying the blockchian based topic mining process for the cognitive computing. As a result of a comparative evaluation between BbMP and BbTMP, it was confirmed that BbTMP shows a performance approximately 3.62% greater than that of BbMP through F-measure.

Table 1 Accuracy of the f-measure analysis results of varying numbers of transaction

Transaction	Blockchain based manufacturing process (BbMP)			Blockchain based topic mining process (BbTMP)		
	Precision	Recall	F-measure	Precision	Recall	F-measure
1000	81.23	84.55	82.85	83.49	90.11	86.67
2000	86.63	82.25	84.38	85.25	90.40	87.74
3000	86.45	84.24	85.33	85.55	89.25	87.36
4000	87.55	84.15	85.81	86.54	86.45	86.49
5000	88.54	84.15	86.28	88.54	87.23	87.88
6000	80.89	86.55	83.62	89.12	84.25	86.61
7000	80.55	86.55	83.44	88.39	86.49	87.42
8000	89.24	80.25	84.50	92.65	83.55	87.86
9000	86.39	82.45	84.37	85.25	90.40	87.74
10,000	88.45	86.25	87.33	91.65	89.25	90.43
Average	85.59	84.13	84.79	87.57	87.52	87.57

5 Conclusion

Population ageing requires a change in the manufacturing process, and there is a fierce global competition to take leadership in the 4th industrial revolution. Personalized production through demand analysis or trend prediction changes a corporate production environment to mass production of limited items. In the cognitive manufacturing industry, it is important to collect, integrate, and process big data with the use of various universal sensors in diverse IoT circumstances. There has been research on the development of a distributed computing platform in the application of blockchain to manufacturing process, banking, financial markets, healthcare, government, insurance, and supply chain. A blockchain standardization forum was established, where many different standards are prepared to support data exchange and system interaction in blockchain network. Therefore, this study proposed a topic mining process in blockchain-based cognitive manufacturing. The proposed method exploits a short-term Fourier transform, which is an effective pre-processing algorithm, and prediction-based maintenance using an error value algorithm in a cognitive manufacturing process. Meanwhile, such data continue to be generated and collected on a large scale. The collected data should be carefully treated as industrial confidentiality or personal information. The blockchain network has a type of distributed storage so that it features difficult forgery and falsification protections, and provides excellent safety. Therefore, it is a critical factor in cognitive manufacturing. Further, in blockchain transaction transmission, information protection and safety are guaranteed. However, because the blockchain includes large data, it has a structural problem. The proposed method can save data into a separate database and map data in the transaction of side chain in block. In case of the blockchain network, only consortium members are able to take part in distributed consensus for creating a new block. The created blockchain and smart device data are saved in a type of distributed ledger into a physically distributed storage for data consistency and management. The mining-based cognitive manufacturing process makes it possible to analyze a variety of data associated with a traceability system, post-by-post scalability infrastructure, and workers' work system through the information exchange of the data collected in real time, and to establish an improved system through data mining.

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