Mechanical Systems and Signal Processing 142 (2020) 106630

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

journal homepage: www.elsevier.com/locate/ymssp

The internet of things-based decision support system for information processing in intelligent manufacturing using data mining technology

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ARTICLE INFO

Article history:
Received 2 October 2019
Received in revised form 20 December 2019
Accepted 7 January 2020

Keywords:
Intelligent decision support system
Data mining
Decision tree

ABSTRACT

To comprehensively understand the decision information system for the information processing of the intelligent manufacturing under Internet of Things, an intelligent decision support system (DSS) based on data mining technology is applied to enterprises to establish an Internet of Things-based intelligent DSS for manufacturing industry, thereby supporting the decision-makers in making intelligent decisions through the intelligent DSS. The research results show that data mining technology can analyze the statistical data from multiple angles and perspectives by modeling, classifying, and clustering a large amount of data, as well as discovering the correlations between the data. Also, in statistical work, the data are counted, and their correlations are utilized to support the decision analysis. Therefore, it can be concluded that the establishment of intelligent DSS for enterprises in manufacturing industry and the utilization of data mining technology as the key technology to achieve the system can make the decision-making of the manufacturing enterprises more effective and scientific. Eventually, the satisfactory decision-making results can be obtained.

1. Introduction

In recent years, database technology has been continuously developed, and the database management systems have been widely applied. As a result, the total amount of data stored in various databases has increased dramatically. However, most of the information is hidden behind these large amounts of data. If the hidden information can be extracted from the database, it can create a lot of potential profits for the enterprises; besides, currently, the competition in various industries is becoming increasingly fierce [1]. Therefore, the way to better organize and manage information becomes more important [2]. The concept of data mining has been developed from such a business perspective and has become a new technology for decision support.

Before the appearance of data warehouse (DW) technology, cyber analytical processing (AP) technology, and data mining (DM) tools, the database used by the decision support system (DSS) can only process and summarize the original data in

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https://doi.org/10.1016/j.ymssp.2020.106630
0888-3270/

general, and it is difficult to convert the original data into useful information, which is inefficient and cannot reveal the trends and tendencies in the hidden data to maximize the availability of valuable information from the data. Therefore, DM technology can provide important knowledge or information to decision-makers and has important economic value. In DM, the stored data often comprises various redundant or incomplete features, which critically decreases the efficiency and the quality of DM algorithms [3]. This kind of thought and method also injected new vitality into DM, which has greatly promoted the development of DM. In the past decade, the research on DM has made great progress. The application of various DM software has greatly promoted the ability to master and process various information and has brought appreciable economic benefits to people. Moreover, in the statistical industry, the quantification and fragmentation of information is a feature of its statistical information, and the way to analyze complex information and effectively manage information is a problem in the traditional statistical industry [4–6]. Compared with the traditional database, characterized by theme-oriented, highly integrated, uneasily lost, and history-reflecting, data contained in DW can solve these problems well; thus, the DW technology can be applied to the statistical industry to solve these problems to a certain extent, thereby greatly improving the analysis and summary functions of the system so that it can help decision-making better and faster.

The DM-based intelligent manufacturing (IM) Internet of Things (IoT) information processing DSS developed in this study can integrate the traditional DSS and management information system into various departments of the society and integrate the current advanced functions of DW and DM to make the operability of the system more humane, the output results meet the management requirements and research of the enterprise, the summary data be reported quickly and comprehensively, and the valuable information hidden in the employees be mined, thereby contributing to the improvement of the enterprise. The successful application of DW and DM technology in many fields provide new ideas for efficient, accurate, and convenient decision support for effective use of information. This system is researched and developed to solve many of the above new problems.

2. Literature review

2.1. Foreign researches

Research by Turker et al. (2019) showed that the widespread application of information technology (IT) in manufacturing has caused the 4th industrial revolution, which enables the data collection in real-world be achieved through manufacturing tools that the IoT communicate with each other [7]. Real-time data also improves the control of manufacturing, especially in dynamic manufacturing environments. In their study, a DSS that aims to improve the performance of scheduling rules in dynamic scheduling was proposed by using the real-time data, thereby improving the general performance of the processing shops. DSS can utilize all kinds of scheduling rules. Its impacts were analyzed to create a simulation model with the literature in the arena and select popular scheduling rules to run. In the case that the number of operations in the waiting line of a workspace in the processing shops dropped to a critical value, DSS can shift the order of the schedules in its previous workspaces to deliver the data to the workspace as rapidly as possible. Therefore, it first determined the operation to be sent to the previous workspace on the workspace in progress and then found the operation with the utmost priority based on the operating scheduling rules; finally, it placed the operation in the 1st position in its line. The performance tests of DSS were carried out with 6 criteria at different rates of low, regular, and high demands. Regardless of the applied scheduling rules, DSS is observed to be able to improve the system performance by increasing the utilization rate of workspaces and reducing the number of late operations and latency.

Research by Kusiak et al. (2018) showed that the manufacturing industry has been evolved and become more automated, computerized, and complicated [8]. IM is an emerging manufacturing mode that combines current and future manufacturing strength with sensors, computing platforms, communication technologies, control technologies, simulation technologies, data-intensive modeling, and forecasting engineering. It takes advantage of the perceptions of networked physical systems led by the IoT, cloud computing, service-oriented computing, artificial intelligence (AI), and data technology. Once is implemented, these perceptions and technologies will make IM a symbol of the next Industrial Revolution. The essence of IM is embodied in 6 supporting industries, which are respectively the technologies and processes, materials, data, predictive engineering, sustainable development, and the resource sharing and networking of manufacturing. The material handling and supply chain have become integral parts of the manufacturing industry. Generally, the section of material handling and transportation is expected to be developed as an integration of manufacturing driven by sustainable development, shared services, and service quality. Future trends in IM include ten conjectures, which range from manufacturing digital and materials – products – process phenomena to the dichotomy and standardization of enterprises. The quality of services and shared services are outlined.

Studies by Abdel et al. (2019) indicated that the education of dissemination of knowledge has become more and more important in the previous several years because of the violent knowledge extension [9]. At the same time, the model of the educational process is being transformed, and the studying methods of different students should be achieved by various means. Thus, an intelligent educational environment is encouraged. It combines different information and communication technologies to activate the studying processes, which are adapted to meet the needs of different students. Through information sensing equipment and information processing platform, the status and activities of different students are continuously monitored and analyzed, and feedbacks from different learning processes of students are provided to improve the learning quality of students. The IoT promises to make a huge difference in personal lives and the productivity of organizations. Through a local intelligent network of widely distributed smart items, IoT can allow the extension and improvement of basic tools in all areas while introducing a new ecosystem to develop applications. The use of the concept of the IoT in all kinds of educational environments can improve the quality of the educational processes so that students can study quickly, and teachers can teach effectively.

2.2. Domestic researches

Bao et al. (2019) proposed that the deficiency ineffectual methods to develop products, processes, and operational models by the integration of virtual and physical environments have led to inadequate property in terms of intelligence, real-time capabilities, and predictability in manufacturing management [10]. A method of modeling and operating digital twins in a manufacturing environment is presented. First, the perception and extension of digital twins (DT) in the context of manufacturing are described, which provides an integration of virtual and physical environments, as well as the implementation of information integration in the factory. Second, the modeling methods for DT, the process of DT, and the operational DT are introduced; next, the interoperability patterns between these DTs are explained. Third, the way to perform operations between products, processes, and resources are introduced in detail; the Automation ML is used to model structural part processing units. Finally, by using the proposed method, a performance evaluation is provided to describe the increase in production efficiency. Both the physical and virtual product data require the connective data for physical and virtual products to hold in a position of the designs, manufacturing, and services of products. Therefore, based on the previous large-scale research, the way to produce and utilize the physical data in a converged network is emphasized and researched to better serve the product life cycle, thereby promoting product design, thereby making the service and manufacturing more efficient, intelligent, and sustainable. Data in product life-cycle management are researched. A new approach to design, manufacture, and service that is driven by DT is presented. Detailed applications and frameworks for the design, manufacturing, and service of digital dual-drive products are studied.

Cheng et al. (2018) suggested that through the investigations of the current Advanced Manufacturing System (AMS), the matching of supply and demand of manufacturing resources is one of the widespread problems that all AMS needs to solve. The method to solve this problem has been transformed from the P2P-based, information center-based, and platform (or system)-matched method to the solutions based on society and services [11]. For the adaption of such trends, by the complicated cyber and IoT structures, a method of supplying and matching is proposed, and a 4-layered architecture that has implemented the method has been designed. Through such a method, IoT technology is used to implement intelligent sensing technology and access to numerous manufacturing resources and capabilities (MR&C), thereby implementing the logical aggregation of numerous MR&Cs that are distributed in the form of services. Afterward, the complicated network models and manufacturing theories are utilized to achieve the efficient management of manufacturing to optimize the configuration and match the supply and demand. Research by Zheng et al. (2018) showed that information and communication technologies are rapidly developing with numerous disputed technologies such as cloud computing, IoT, big data, and AI [12]. Such technologies permeate the industry of manufacturing, and the integration of physical and virtual data through the Cyber-Physical System (CPS) marks the emergence of the 4th stage of industrial manufacturing (i.e. the Industry 4.0). The widespread utilization of CPS in manufacturing environments has made manufacturing systems more intelligent. To enhance the research of Industry 4.0, the IM system of Industry 4.0 is explored. First, the conceptual framework of the Industrial 4.0 IM system is introduced. Second, the intelligent processing scenarios related to intelligent design are demonstrated, intelligent control, intelligent monitoring, and intelligent scheduling is introduced. Based on these demonstration scenarios, the crucial technologies of the IM system and their possible applications in the age of Industry 4.0 are evaluated.

Ren et al. (2019) proposed a workshop material delivery framework by the big data of real-time manufacturing and studied the crucial technologies of the proposed framework [13]. First, an answer for data sensing and collection is given. Second, methods for big data manufacturing, preprocessing, and storage is given to integrate and communicate the data of manufacturing with a unite format for the guarantee of data re-usability. Third, a graphical model of DM for manufacturing is proposed. The enhanced Apriority-based association analysis model is used to categorize the frequency trajectory of material transport. From the perspective of the framework implementation, a proof of perception approach is provided. The major findings and insights of the experimental results are summarized as management suggestions, which can help the manufacturers make better decisions for shop floor management. A graphical model of manufacturing big DM is proposed. Li et al. (2018) proposed that the introduction of ubiquitous instruments in the IoT can achieve unprecedented real-time visibility (instrumentation), grid, transportation, transportation, water, oil and gas optimization, and fault tolerance, and examples were given [14]. By connecting these different physics, people, and business worlds with ubiquitous instruments, even in the nascent stage, it is possible to create more intelligent, more efficient, more comfortable, and safer IoT solutions. An important new direction to realize this potential is to develop a comprehensive model of this system that dynamically interacts with instruments in the feedback control loop.

In summary, many domestic and foreign researchers have studied intelligent DSSs and implemented enterprise DSSs. Domestic research on enterprise intelligent DSSs is far from mature compared with foreign research. However, with the attention of the government, enterprises and the public, the growing awareness of the importance of intelligent decision-making, and the computer technology, especially DM techniques applied in enterprises, the establishment of intelligent DSSs have become the basis for the improvement and development of each enterprise.

3. Research on the algorithms of DM

3.1. Association rule mining (ARM)

Association rule is one of the main technologies of DM. Association rules are used to find out the connections between different features in the database. The association rule-based DM has been successfully applied in various fields such as commerce.

If the association considered by the rule only involves either the existence or non-existence of the item, it is called the Boolean Association Rule (BAR). Data processed by BAR are discrete and categorized. If the association considered by the rule involves the quantized items, it is called the Quantitative Association Rule (QAR).

Association rules consist of multi-level and mono-level rules. For instance, cola drinks and a specific brand of cola drinks (such as Coca-Cola and Pepsi) are not in the same abstraction layer. If the association rules involve items in different abstraction layers, it is multi-leveled; otherwise, it is a mono-layer association rule [15]. An ARM can be extended to correlation analysis and mining of maximum frequent set patterns and frequent closed items collection.

Being one of the most active analysis methods in DM algorithms, association rule aims at finding the relations of items in a dataset, while such relations are indirectly expressed in the data [16]. The number of items included in a project set is considered as the dimension of this project set or the length of the project set. A set of items in length k is called a set of k-dimensional items.

$$c(X, Y) = \frac{s(X \cup Y)}{s(X)} \tag{1}$$

Fundamentally, an association rule implies $X \Rightarrow Y$, where $X \subset I$, $Y \subset I$, and $X \cap Y = \Phi$. In the transaction database D, the provision of the association rule $X \Rightarrow Y$ is the proportion of transaction quantity that contains X and Y in the dataset to the quantity of all transactions, which is expressed as support ($X \Rightarrow Y$), as the following equation indicates:

$$\text{support}(X \Rightarrow Y) = |\{T : X \cup Y \subseteq T, T \in D\}|/|D| \tag{2}$$

$$\text{confidence}\,(X \Rightarrow Y) = |\{T : X \cup Y \subseteq T, T \in D\}|/|\{T : X \subseteq T, T \in D\}| \tag{3}$$

If support ($X \Rightarrow Y$) is equal to the minimum support (min-supp) and the minimum confidence ($X \Rightarrow Y$) (min-conf), the association rule $X \Rightarrow Y$ is considered as a strong rule; otherwise, it is considered as a weak rule.

ARM aims at finding all the strong rules in database D. The item set corresponding to the strong rule $X \Rightarrow Y$ must be a frequent itemset (FIS).

The Apriority Algorithm (AA) mainly implements 2 operations: generating potential candidate sets, then removing infrequent candidate sets according to properties, and finally generating eligible item sets. Typically, the value of provision is set to 10%, while that of confidence is set to 80%.

So far, many improved algorithms in conformity with the AA have been proposed.

Following AA of the hash table, the space occupied by the candidate k-term set C ($k > 1$) is effectively reduced by constructing a hash table.

First, the data partitioning technique is divided into n blocks; then, the FISs satisfying the minimum support threshold are respectively searched in the block, which is called a local frequent itemset [17]. Then, the local FISs of all n blocks are used as the candidate set of the entire database, and the second stage of scanning is performed. Finally, the overall FISs are obtained.

Through the sampling operations, a subset of a given dataset is mined. S sample sets are randomly collected from the database D during the sampling process; then, S is used as the data set object, and the minimum support degree is set for scanning to find the FIS [18]. It should be noted that the minimum threshold of the provision is lower than that for overall DM.

3.2. The mining algorithm for the decision tree (DT) in DM

Similar to the structure of trees, each leaf-node of DT corresponds to a category, while the non-leaf-nodes of DT correspond to a certain feature. The sample is divided into several subsets according to different values of the features on the attribute. The core problem in constructing a DT is the way to choose the appropriate features to divide the samples at each step [19]. In terms of a classification problem, learning and constructing a DT from a training sample of known class markers is a top-down process of divide-and-conquer.

In terms of how the DT is built and predicted, the CART classification tree uses the category with the highest probability among the leaf nodes as the prediction category of the current node. The regression tree output is not a category; it uses the mean or median of the final leaves to predict the output.

The classification DT and regression DT are 2 major divisions of DT. The classification DT generates trees for discrete datasets. The regression DT generates trees for continuous variables. The generation process of DT is shown in Fig. 1.

The leaf-node represents a feature value of the category to which the record corresponding to the path from it to the tree root belongs. The non-leaf nodes are associated with non-class features with the greatest amount of information, and the

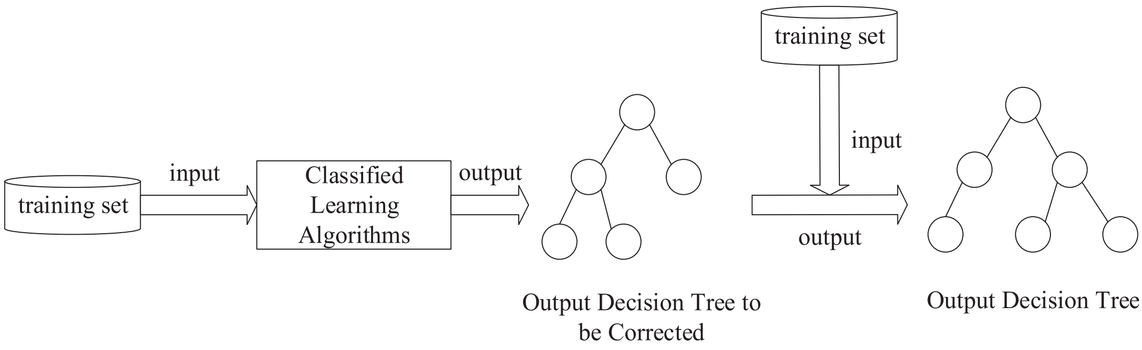

Fig. 1. The generation process of the DT.

optimal features that can classify the samples are selected by using information gain [20]. The algorithm minimizes the number of tests for object classification and ensures that a smaller tree is found to represent the relevant information. The specific running time is shown in Figs. 2 and 3.

In the DT mining method, in addition to establishing the DT, it is also essential to consider the correctness of the DT and to prevent the DT from being excessively large. There are many reasons for these problems. The incorrect description of language will increase the complexity of DTs. The noise and inconsistency in data are also one of the reasons. To solve these problems, the DT pruning technology is needed [21]. The pruning techniques include the pre-pruning and post-pruning.

If the target feature has n different values, the information entropy of the training sample set S relative to the category of the n states is defined as:

$$\mathrm{Entropy(S)} = -\sum_{i=1}^{n} \mathrm{p(X_i)log(p(X_i))} \tag{4}$$

It is assumed that the occupation of the k-th sample in the current sample database D is $\mathrm{p_k} = (\mathrm{k} = 1, 2, \ldots, |\mathrm{y}|)$ and the information entropy of D is defined as

$$\mathrm{Ent(D)} = -\sum_{\mathrm{k}=1}^{|\mathrm{y}|} \mathrm{p_k log_2 p_k} \tag{5}$$

A smaller value of Ent(D) indicates a higher purity of D.

$$\mathrm{Gain(S,A)} = \mathrm{Entropy(S)} - \sum_{\mathrm{v}\in \mathrm{V(A)}} \frac{|\mathrm{S_v}|^*}{\mathrm{S}} \mathrm{Entropy(S_v)} \tag{6}$$

In the above equation, S refers to the training sample set. A larger information gain indicates a smaller entropy; thus, the certainty is high.

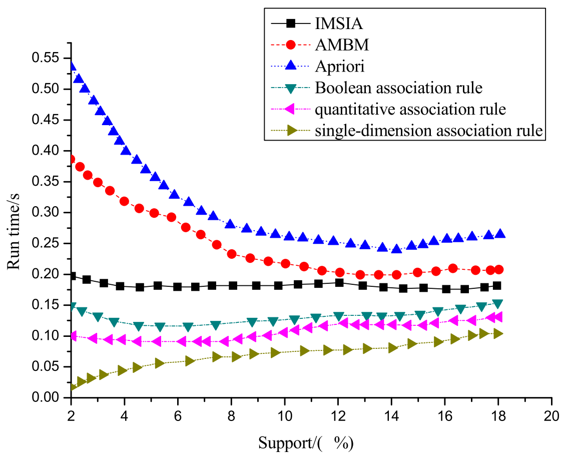

Fig. 2. The run time under different support levels.

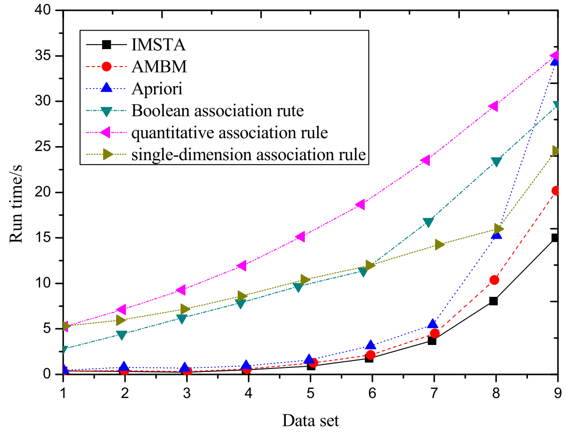

Fig. 3. Algorithm run time for different data sets with the same degree of support.

4. Analysis of information DSS of intelligent manufacturer Internet of Things

4.1. Analysis of the DSS for the Internet of Things information processing

The decision-making analysis information support system has 2 construction goals: based on the standard classification system and the social-economic indicator system, the socio-economic statistical information is applied, and the modeling and classification of data are achieved through DW technology. First, the decision-making statistical information support the system database processed by government IoT information is established. Then, by assembling and managing the database, the hidden knowledge between the information is mined, the DT is constructed, and the leadership decision information support system is finally established [22]. Thus, the safe and efficient decision support is provided for the governors through the construction and application services of the system. In the statistical analysis system for decision-making processed by IoT, the critical software and hardware environment for the content management system (CMS) is constructed. Also, the CMS of the statistical analysis system for decision-making is developed by using the TRSWCM software and Java Server Page (JSP) technology. The scientific and reasonable website technical standards are constructed, and the scientific workflows for collection, edition, verification, and publication are constructed, which can provide communication port for administrative departments of statistical information with different administrative ranks and business processing offices with different professions, thereby the sources of statistical information are ensured, as the analysis of information DSS shown in Figs. 4–6.

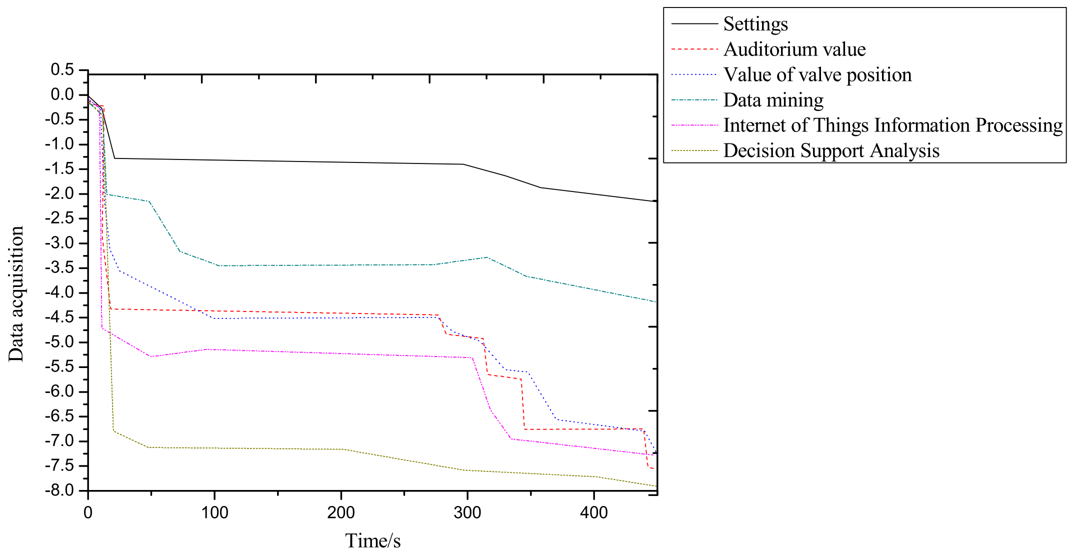

Fig. 4. Information decision support analysis (1).

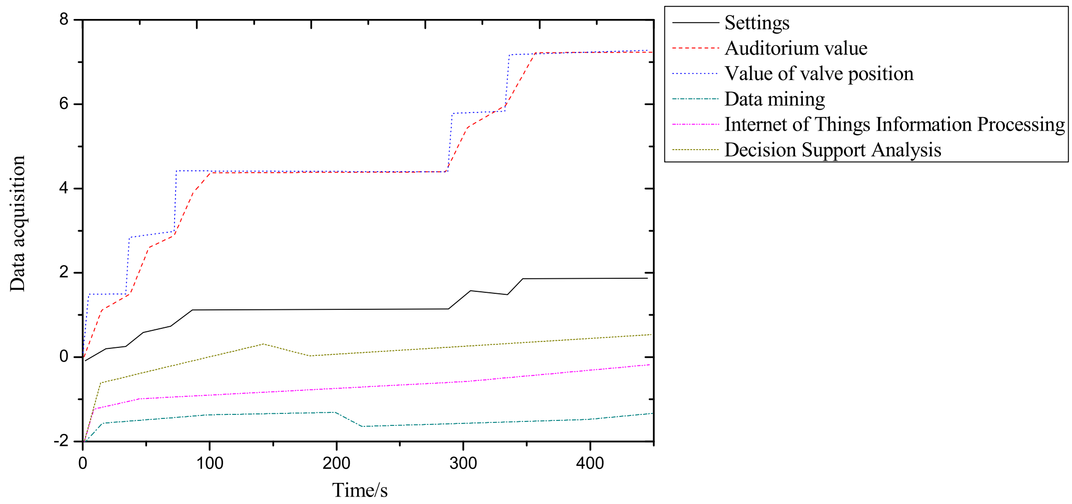

Fig. 5. Information decision support analysis (2).

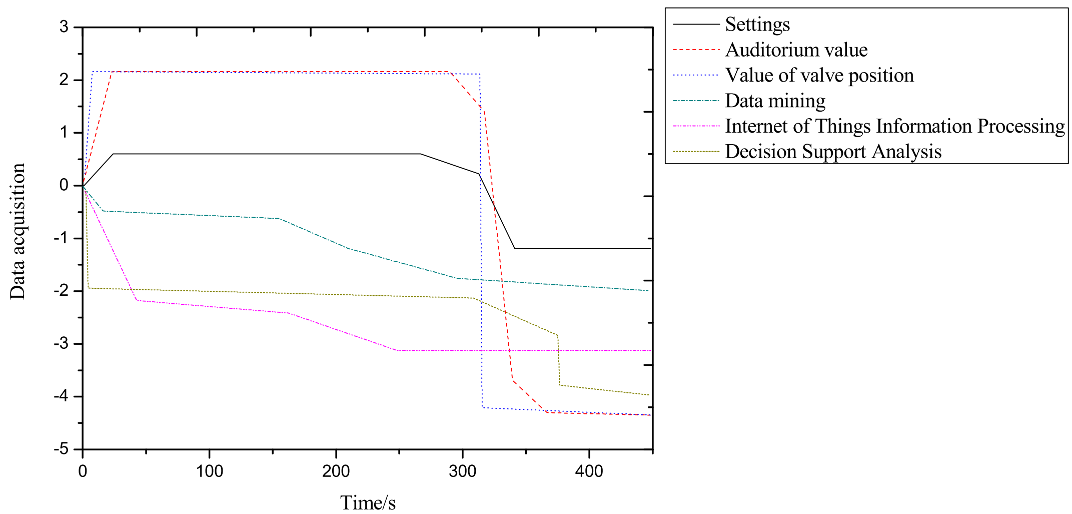

Fig. 6. Information decision support analysis (3).

The system has established a variety of subject databases, DWs, a variety of tools, and a variety of DM application models, such as multivariate statistical analysis, time series, graphical analysis, and other DSSs [23]. According to different needs, the multi-objective, multi-angle, and deep-level processing, analysis, prediction, mining, and display of statistical data provide analysis and decision support for the economic operation and social development of the enterprise, as the information decision support analysis (4) shown in Fig. 7.

The visualization of IoT big data analysis can be presented to IoT users in a very intuitive form, making it easier for IoT users in different industries to extract valuable knowledge, as well as helping users make the most appropriate decisions [24]. IoT application is related to the national economy, the livelihood of people, and life safety timeliness, which has high requirements on the timeliness, reliability, and credibility of DM results. DM algorithms must be studied by big data experts and industry experts. The predictive analysis of IoT applications is very important. It is necessary to organize research teams combining industry experts, IoT experts, and big data experts to study prediction models and algorithms that adapt to the IoT big data in different industries [25]. Networking requires a new set of theories and methods to standardize and flexibly organize various data resources distributed geographically, which is convenient for users to search for keywords, tag keywords, or other input semantics to improve the ability to actively acquire knowledge. The aggregation of raw data perceived by different sensors, multi-dimensional data fusion, multi-user collaborative sensing, and data quality management makes the processed results more accurately reflect the reality, which is the focus of research on big data of the IoT, as the support analysis (5) shown in Fig. 8.

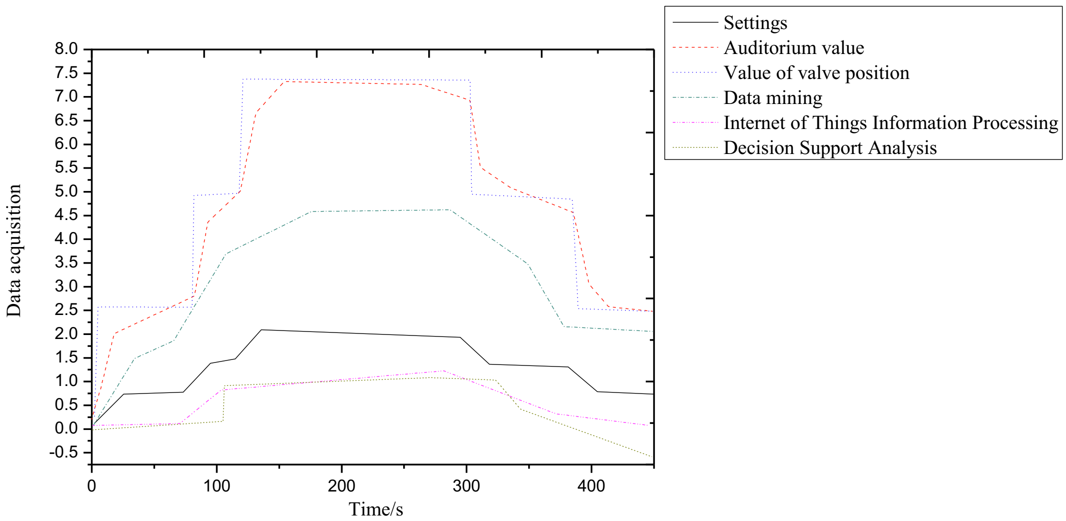

Fig. 7. Information decision support analysis (4).

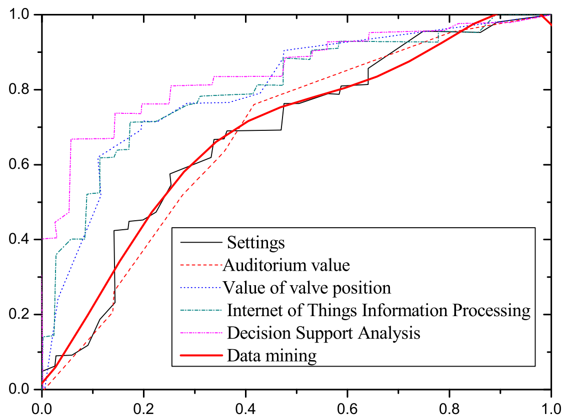

Fig. 8. Information decision support analysis (5).

4.2. Analysis of the DSS under DM

The data in the DW often come from a variety of completely different data collection paths. DW technology should be cleaned and organized to make these data accurate, consistent, and easy to be queried efficiently [26]. Unlike database technology applications, the DW is more of an integrating and data-analyzing process that is distributed throughout a certain organization instead of a product that is available on the market directly [27]. For specific DW systems with different business needs, processes and scales, the corresponding reduction and the adjustment process are required, as the information decision support analysis (6) shown in Fig. 9.

As the analysis of data information shown in the above figure, the information analysis conforms with the application of DM technology, such as the standard reports, statistical charts, thematic flexible query, multi-dimensional analysis, deep analysis, and forecasting [28]. If the transaction database remains unchanged, while the values of min-supp and min-conf are changed, to discover the previously unknown association rules, the user must gradually adjust the 2 thresholds of min-supp and min-conf to focus on the truly valuable association rules, which is a dynamic interaction process [29]. In the case that the value of min-supp changes, some of the origin FISs may lose the min-supps, while some of the origin non-FISs may gain, as the data analysis of DSS shown in Fig. 10.

As the Internet technology and software developing-structure keep being enhanced, the currently popular Browser/Server (B/S) structure and the 3-layered client/server architecture can provide a good framework for the CMS construction, which is the optimal selection for CMS construction as well [30]. In terms of B/S structure implementation, the .net technology is selected as the developing environment for the software background. The selection of .net as the developing platform for CMS is due to the reasons that the CMS can be installed in the Windows 2003 Server system where the current database

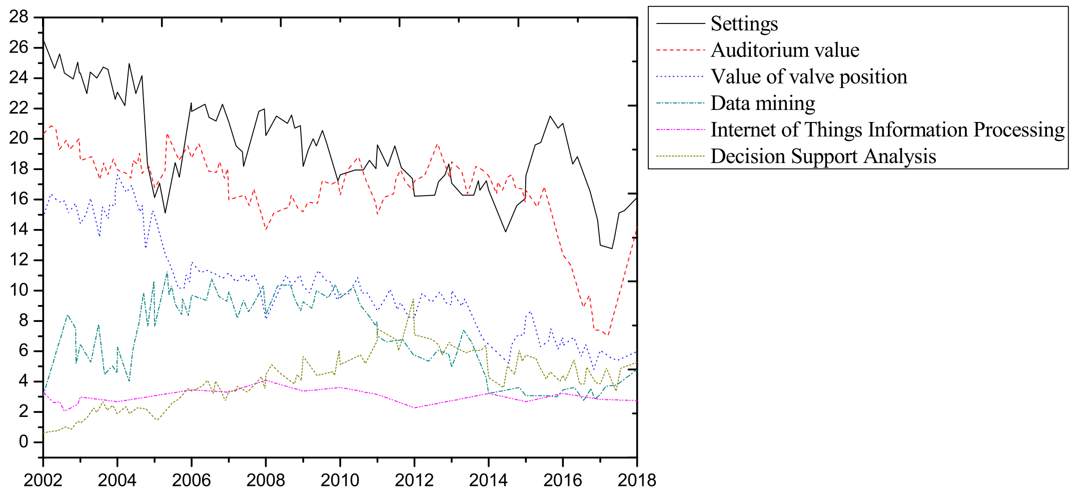

Fig. 9. Information decision support analysis (6).

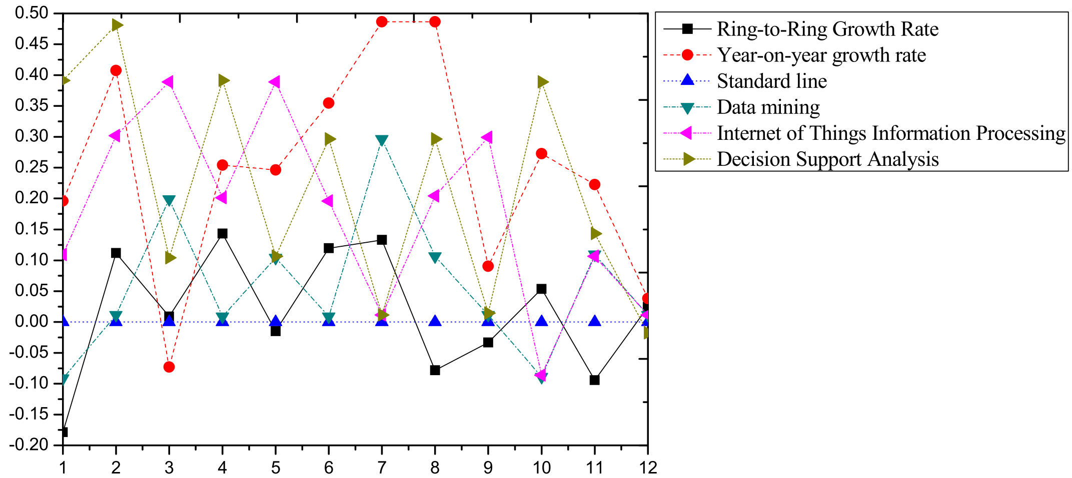

Fig. 10. Income data analysis by the DSS.

server of the statistical system exists. Therefore, by the installation, the existing resources can be effectively utilized and applied to CMS according to the requirements of different scales. The technical aspects mainly involve 3 aspects: the construction of the statistical analysis support system portal, the retrieval of textual information, as well as the input and collection of information. The formulation of the process is shown in the technical analysis of the DSS in Fig. 11.

DW system implementation is a process of continuous cycling and continuous development. When a business officer creates value for the enterprises in the process of using the DW, more detailed data and necessary summary data will be constantly required to be entered into the DW for analysis [31]. The capacity of the DW and its performance requirements are also a factor that DW managers need to consider [32]. It can find generalized knowledge, differential knowledge, predictive knowledge, etc. It can also analyze data with a high degree of automation, make induction and reasoning, and predict future trends and behaviors. Therefore, users can realize the true value of data to achieve better decision support for people.

Predictive DM can use the value of a data item to determine the result, resulting in an exact value that is known. Descriptive DM is a description of the rules in the data, or the data is grouped with the similarity of the data; however, it cannot be used directly for prediction.

The utilization of DW, intelligent analysis, and DM technologies to realize intelligent processing of business data can discover and contain hidden information, establish enterprise-level business analysis and DSS, and provide timely and accurately scientific decision-making basis for market operation, thereby establishing a strong operational analysis and DSS platform, realizing the top-down analysis, management and decision support within the entire business scope of the enterprise, enhancing the core competitiveness of the enterprise, and enabling the enterprise to compete in the increasingly fierce market with a dominant position.

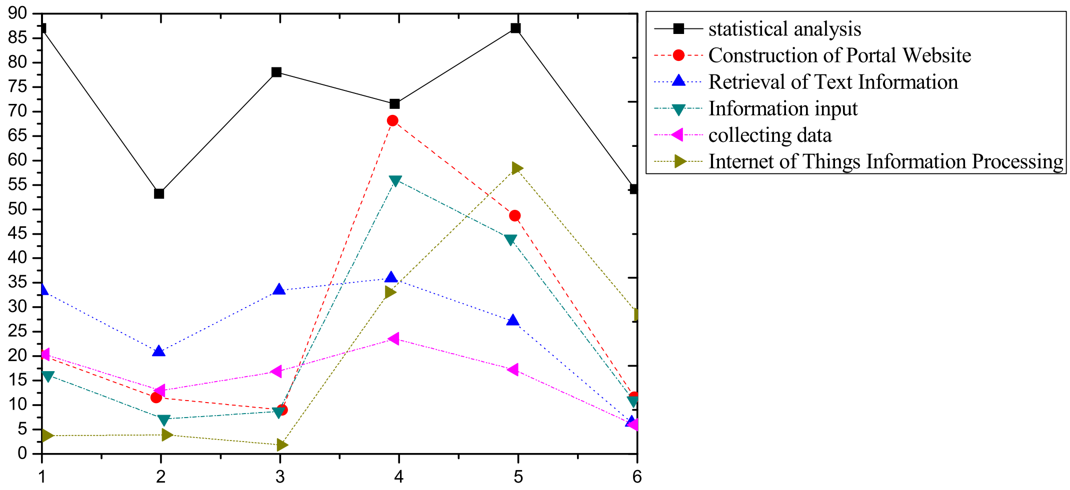

Fig. 11. Technical analysis of DSS.

5. Conclusions

To comprehensively understand the decision information system for the information processing of the intelligent manufacturing under Internet of Things, the DM technology is comprehensively researched first. DM technology can provide important knowledge or information for decision-makers and has important economic value. Besides, an intelligent manufacturing IoT-based DM model for the information processing DSS is proposed. Several commonly seen DM algorithms are analyzed, such as ARS and AA. The DT mining algorithm is researched, the generation of several DTs is analyzed, as well as the DT pruning algorithm. Besides, the information processing DSS of the intelligent IoT for enterprises is designed and implemented, whose functional needs are analyzed as well. The implementing technologies, general designs, including the system structural design and general database design, and the functional modules are determined and designed, which helped the realization of the information processing DSS of intelligent manufacturing IoT for enterprises.

However, due to the limitations of time and resources, the research on the information processing DSS of intelligent manufacturing IoT for enterprises is not perfect, which should be improved from multiple aspects. For example, DM technology can be further researched to better demonstrate the intelligence of the DSS.

CRediT authorship contribution statement

Yuan Guo: Methodology, Project administration. **Nan Wang:** Writing - original draft, Writing - review & editing. **Ze-Yin Xu:** Software. **Kai Wu:** Validation.

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.

Acknowledgement

This research is supported by Anhui Provincial Natural Science Foundation (1808085ME126), the Provincial (Key) Natural Science Research Project of Anhui Colleges (KJ2017A539), Talent Research Fund Project of Hefei University in 2016-2017(16-17RC25), the Support Program Project for Excellent Youth Talent in Higher Education of Anhui Province (gxyq2018069).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ymssp.2020.106630.

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