Data Mining Technology Used in an Internet of Things-Based Decision Support System for Information Processing Intelligent Manufacturing

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Abstract

In recent years, database technology has improved significantly, and database management systems have gained widespread adoption. As a result, the volume of data saved across numerous databases has increased exponentially. However, the vast majority of information is hidden beneath this mountain of data. The goal of this study is to get a comprehensive understanding of the decision information system employed in the Internet of Things for intelligent manufacturing data processing. The proposed Decision support system (DSS) information processing is accomplished through the use of an IoT-based intelligent manufacturing data mining model. Numerous DM algorithms that are frequently encountered are analyzed, including the ARS and Apriori Algorithm (AA). The Decision Tree data mining algorithm is investigated, as is the generation of several Decision Trees and the pruning algorithm for digital twins. The findings demonstrate that data mining technology is capable of analyzing statistical data from a variety of angles and perspectives by modeling, classifying, and grouping large amounts of data as well as discovering correlations between them. Additionally, statistical work involves the calculation of data and the use of their correlations to aid in decision analysis. The proposed theoretical framework demonstrates how DSS-integrated components can work cooperatively in Intelligent Manufacturing to define a stable data flow within the Internet of Things. Particular emphasis is placed on conceptualizing the decision support system's integrated performance.

Keywords: Data Mining; IoT; ARS; Apriori Algorithm; Decision Support Systems

1. Introduction

Manufacturing systems rely heavily on information and communication technology. The ongoing development of cyber systems and related intelligent and smart technologies [1–4] has given rise to big data, Industry 4.0, the Internet of Things (IoT), cloud computing, cyber–physical systems (CPSs), digital twin (DT), and next-generation artificial intelligence (AI). Numerous advanced manufacturing paradigms have been presented that include these notions in order to provide manufacturing processes and systems with a measure of "intelligence" or "smartness. In recent years, major nations have emphasized the significance of transforming and upgrading their manufacturing sectors, focusing society's attention on digitization, networking, and industrial intelligence/smartness. Educational and commercial studies have discovered two words to describe manufacturing's significant integration with advanced information/cyber technologies: smart manufacturing (SM) and intelligent manufacturing (IM).

In recent years, database technology has improved significantly, and database management systems have gained widespread adoption. As a result, the volume of data saved across numerous databases has increased exponentially. However, the vast bulk of information is hidden behind this mountain of data. The goal of this study is to get a comprehensive understanding of the decision information system employed in the Internet of Things for intelligent manufacturing data processing. The proposed Decision support system (DSS) information processing is accomplished through the use of an IoT-based intelligent manufacturing data mining model. Numerous DM algorithms that are frequently encountered are analyzed, including the ARS and Apriori Algorithm (AA). The Decision Tree data mining algorithm is investigated, as is the generation of several Decision Trees and the pruning algorithm for digital twins. The findings illustrate that data mining technology is capable of examining statistical data from a number of viewpoints and angles by modeling, categorizing, and grouping vast volumes of data and uncovering relationships between them.

With the arrival of a new round of industrial revolution, information technology has accelerated its integration with manufacturing systems, and the data owned by enterprises have become increasingly rich, with features of volume, variety, and velocity [1]. Commercial data helps enterprises to not only accurately recognize changes in their internal and external environments, but to conduct science research and decision making in order to optimize production processes, save expenses, and improve productivity. With massive data, new business models are generated out of expectation (such as mass customization [2] and precision marketing [3]) to empower social development and economic growth. As a result, large industrial data is viewed as a tool for enabling intelligent manufacturing. With the development of artificial intelligence, big data analytics (BDA) have been greatly improved to effectively mine both structured and unstructured industrial data in intelligent manufacturing, which has become a new research hotspot [4]. Continuous learning from big data of manufacturing systems enables the system to be self-learning, self-optimization and self-regulation [5]. Additionally, statistical work involves the calculation of data and the use of their correlations to aid in decision analysis. The proposed theoretical framework demonstrates how DSS-integrated components can work cooperatively in Intelligent Manufacturing to define a stable data flow within the Internet of Things. Particular emphasis is placed on conceptualizing the decision support system's integrated performance.

2. Literature Review

Turker et al. [7] demonstrated that broad adoption of information technology (IT) in manufacturing ushered in the fourth industrial revolution by facilitating the collection of real-world data via IoT-connected production machines. Additionally, real-time data enables improved manufacturing control, which is particularly advantageous in dynamic industrial contexts. They offer a DSS in their work for increasing the performance of scheduling rules in dynamic scheduling by exploiting real-time data, consequently boosting the overall performance of the processing store [7]. DSS is capable of utilizing a diverse set of scheduling rules [8]. The influence is analyzed in order to develop a simulation model based on the field's current literature and to run popular scheduling rules. When the number of operations in the processing store's workspace queue exceeds a critical level, the DSS can reshuffle the schedules in the preceding workspace in order to accelerate data delivery to the workspace. As a result, it determines which operation should be transmitted to the previous workspace on the current workspace first, then which operation has the highest priority according to the operation scheduling rule, and finally, it inserts the operation in the top position in its row [9]. Six criteria are utilized to assess DSS performance under three distinct demand conditions: small, normal, and large. DSS was demonstrated to improve system performance regardless of the scheduling rules used by increasing workspace utilization and minimizing the amount of late operations and delays.

According to Kusiak et al [10] research, manufacturing has grown into a more automated, computerized, and sophisticated process. Intelligent Manufacturing (IM) is a new manufacturing mode that leverages sensor, computing platform, communications technology, control systems, simulation software, information modeling, and forecasting techniques to combine present and future manufacturing strengths. It takes advantage of the networked physical system awareness enabled by the Internet of Things (IoT), cloud computing, service-oriented computing, artificial intelligence (AI), and data technologies [11]. When completely deployed, these attitudes and technology will elevate information management to the rank of the new Industrial Revolution's defining emblem. The essence of information management is embodied in six related industries: technology and process, resources and data, predictive engineering, sustainable development, and resource sharing and manufacturing networks. Material handling and supply chain management have become inextricably linked to manufacturing. In general, the material handling and transportation market is predicted to mature into a manufacturing integration centered on sustainable development, shared services, and service quality. Ten theories on possible information management developments range from digital manufacturing and materials-products-process phenomena to dichotomy and organizational standardization. The essay discusses the significance of service quality and the shared services idea.

According to Abdel et al. [12], knowledge dissemination education has grown in importance in recent years as a result of the expansion of knowledge about violence. Simultaneously, the educational process is evolving, necessitating the implementation of diverse techniques of student learning. As a result, an educational environment that is sensible is promoted. It utilizes a variety of information and communication technologies to provide each student with a personalised learning experience. The status and actions of various students are continuously monitored and evaluated using information sensing equipment and information processing platforms, and feedback from various student learning processes is offered to help students learn more effectively. The Internet of Things has the potential to greatly boost individual and organizational productivity [13]. By establishing a new environment for generating applications via a local intelligent network of widely distributed smart things, IoT can enable the expansion and refinement of fundamental tools in all sectors. Incorporating IoT concepts into all types of educational environments has the potential to improve the quality of the educational process by helping students to learn more rapidly and teachers to teach more effectively.

3. Research Method

3.1. Association rule mining (ARM)

Association norms are an integral part of DM. Association rules are used to establish a connection between different database features. DM based on association rules has been effectively utilized in a variety of industries, including commerce. If simply the existence or absence of an item is considered, the rule is referred to as a Boolean Association Rule (BAR) [14]. BAR processes data in a distinct and categorical manner. When a relationship involving a quantized object is considered, the rule is referred to as the Quantitative Association Rule (QAR). Multi-level or mono-level association rules exist. Coca-Cola beverages and specific Coca-Cola beverage brands (such as Coca-Cola and Pepsi) are excluded from the same abstraction layer. If the association rule involves elements from distinct abstraction layers, it is multi-level; otherwise, it is a mono-layer association rule [15]. ARM can be used to extend correlation analysis and pattern mining on maximum frequency sets and frequent collections of closed items. Association rules, as one of the most active analytical strategies in the DM algorithm, strive to uncover relationships between items in a dataset when the relationship is expressed in an indirect fashion in the data. The dimensions or length of a project set refers to the amount of objects contained within. The term "k-dimensional item set" refers to a collection of items with a length of k. The formula for association rule mining (ARM) is as follows:

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

In general, the association rule states that X → Y, where X ⊂ I, Y ⊂ I, and X ∩ Y = Φ. The association rule X → Y in the transaction database D is the ratio of the amount of transactions containing X and Y in the dataset to the total quantity of transactions, which is represented as support (X → Y), as the following equation demonstrates:

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

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

If the support (X Y) equals both the minimal support (min-supp) and the minimum confidence (X → Y) (min-conf), it is termed strong; otherwise, it is considered weak. ARM's objective is to detect all strong rules that exist in database D. The set of items that meet the stringent requirements X → Y must be a frequently occurring itemset (FIS). The Priority Algorithm (AA) conducts two operations: it generates a set of prospective candidates, filters out candidate sets that rarely meet the property, and then generates a collection of eligible items. Typically, the provision amount is 10% and the confidence value is set at 80%. Numerous improvements to AA-based algorithms have been presented thus far. By implementing the hash table's AA, the candidate set of k-term C (k > 1) occupies significantly less space. To begin, the data partitioning technique separates the data into n blocks; next, for each block, FIS that satisfy the minimal support threshold are found, forming the local frequent itemset. A second stage of scanning is then done, this time using the local FIS of all n blocks as the candidate pool for the full database. Finally, the FIS is totaled. To extract a subset of a given dataset, a sampling process is employed. During the sampling procedure, the sample set S was randomly picked from database D; S is then used as the data set object, and the scan to identify FIS is run with the minimal support degree set to 1. It's worth mentioning that the preliminary minimum for total DM is lower.

3.2. Mining algorithm for decision tree (DT) in data mining

As with the tree structure, each DT leaf node denotes a category, whereas the non-leaf DT nodes denote a particular attribute. The sample is subdivided into numerous subgroups according to the various values of the attribute [16]. The key challenge in designing the DT is deciding which characteristics to utilize to divide the sample at each step. When it comes to classification difficulties, the process of learning and developing a DT from a training set of known class markers is a top-down divide-and-conquer technique. Regarding the formation and prediction of DTs, the CART classification tree allocates the prediction category for the current node to the category with the highest probability among leaf nodes. The output of the regression tree is not a category; rather, it predicts the output based on the mean or median of the preceding leaf [17].

The two core divisions of DT are classification and regression. For discrete datasets, the DT classification method constructs trees. For continuous variables, DT regression generates a tree [18]. The method of creating a DT is illustrated in Figure 1. Both the feature value associated with the category to which the record belongs and the path connecting it to the tree's root are encapsulated in the leaf-node. The non-leaf node is linked with the non-class feature that contains the most information, and the best feature capable of classifying the sample is chosen using information gain. The approach reduces the number of item categorization tests performed and ensures that the essential information is represented by a smaller tree. The figures 2 and 3 depict the specific running time.

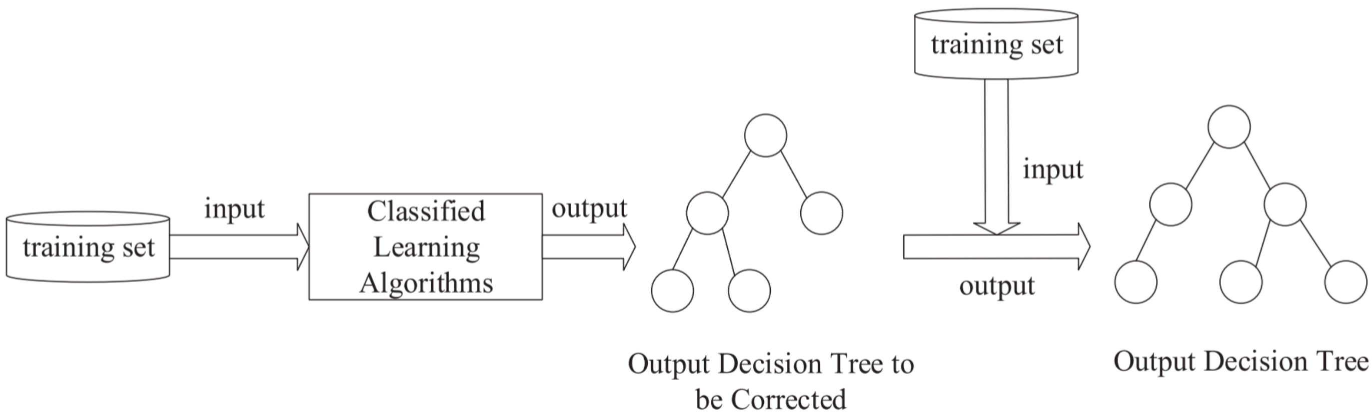

Fig. 1. DT development process.

Apart from determining the DT, it is critical to consider the DT's correctness and to avoid the DT growing too large [19]. There are numerous possible causes of this issue. Incorrect language description adds to DT's complexity. Noise and inconsistency in data are also factors. DT pruning technology is required to address these issues. Pre- and post-trimming are two techniques for trimming. If the target feature has n distinct values, the training sample set S's information entropy with respect to the n state categories is defined as:

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

It is assumed that the occupancy of sample k in the current sample D database is p_k = (k = 1, 2,....,|y|) and the entropy of information D is defined as:

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

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

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

S denotes the training sample set in the preceding equation. Increased information gain implies decreased entropy; thus, the degree of certainty is high.

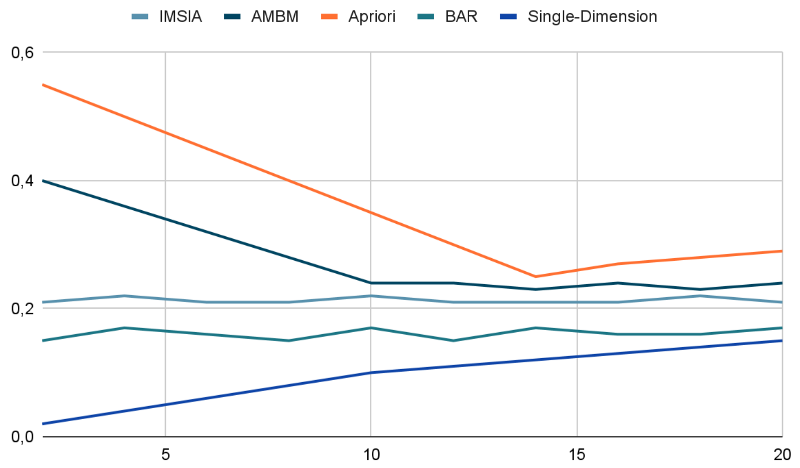

Fig. 2. Time runs under different support levels.

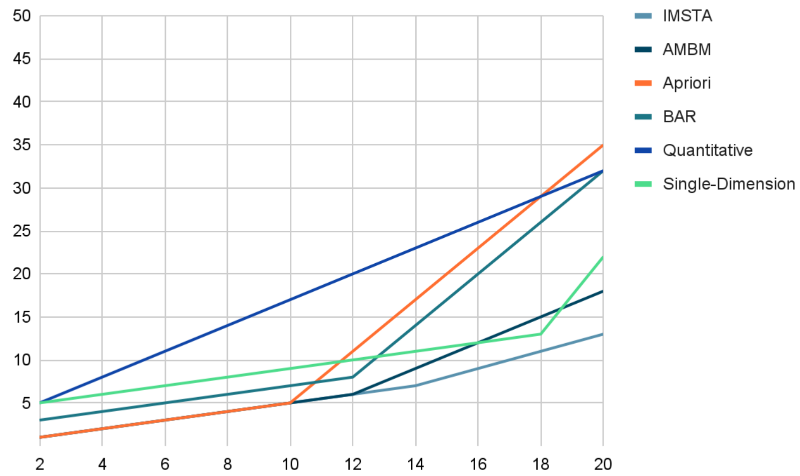

Fig. 3. Algorithm runtime for different data sets with the same level of support.

4. Results and Discussion

4.1. Analyses of the DSS for information processing in the Internet of Things

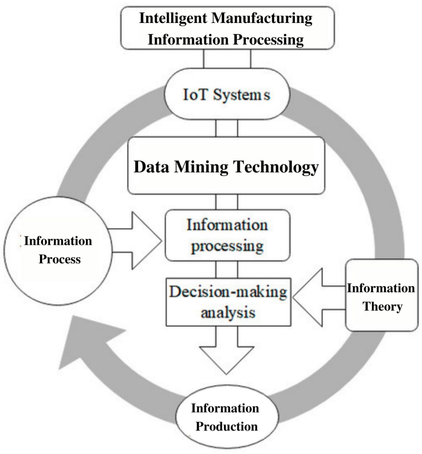

Fig. 4. The operating mechanism of Intelligent Manufacturing-IoT in the information production stage.

The decision support analysis information system is constructed with two purposes in mind: socioeconomic statistics information is used, and data modeling and classification are accomplished using DW technology [20]. The flow of the research process in this study is depicted in Fig. 4 above. To begin, decision-making statistics serve as the foundation for the system database that the government's IoT information architecture processes. Following the creation and monitoring of the database, hidden knowledge is mined, the DT is constructed, and finally, a performance and decision information support system is developed. Thus, governors benefit from construction services and system applications that enable them to make decisions safely and quickly [21]. In statistical analysis systems for IoT-driven decision-making, critical software and hardware configurations for content management systems (CMS) are built. Additionally, a content management system (CMS) for the decision-support statistical analysis system was developed using TRS WCM and Java Server Page (JSP) technologies. The article defines scientific and technological criteria for websites, as well as scientific methods for data collection, editing, verification, and dissemination. These standards and procedures can act as a communication hub for statistical information administration departments at various administrative levels and business processing offices at various levels of specialization. Thus, the source of statistical data may be determined, such as the DSS analysis of the data in Fig. 5–7.

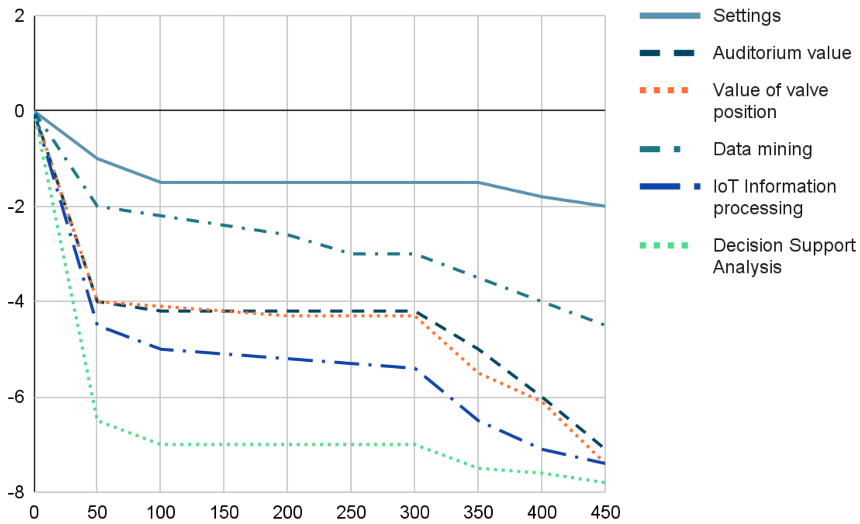

Fig. 5. Analysis of informed decision support.

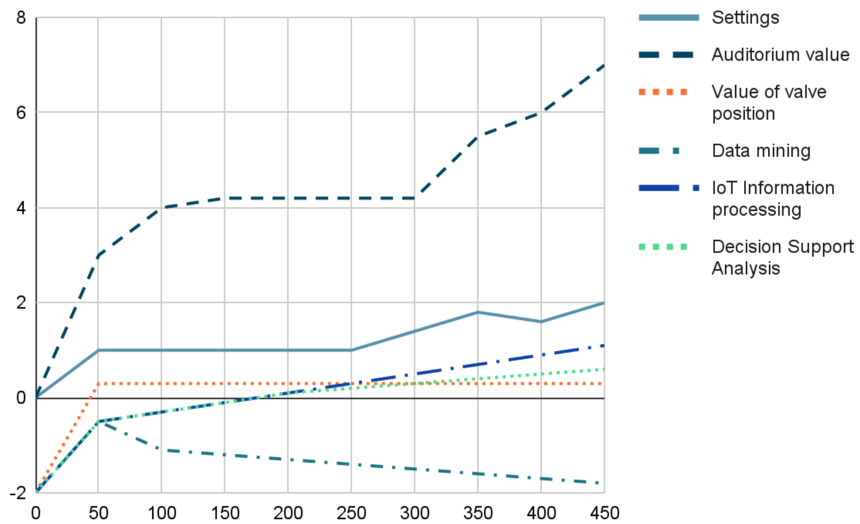

Fig. 6. Analysis of decision support information second result

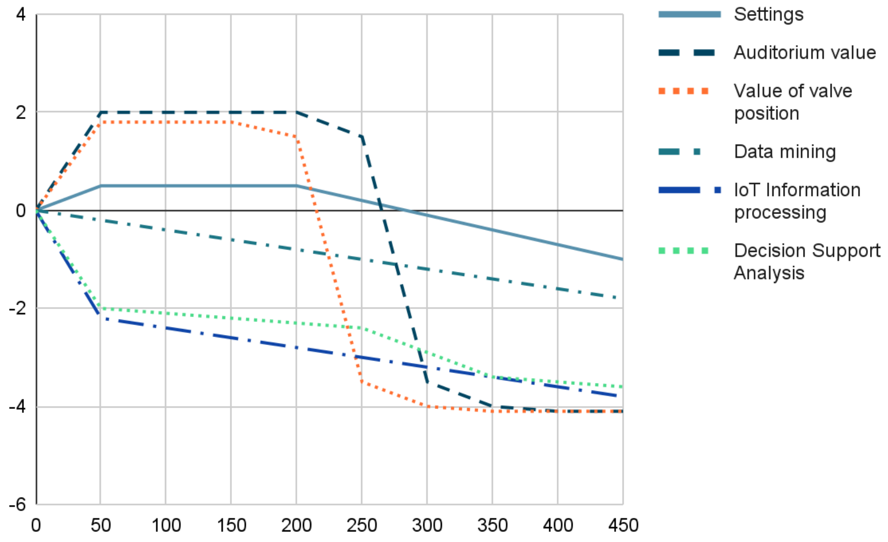

Fig. 7. Analysis of information decision support third result

The system has built a number of subject databases and data warehouses, as well as a variety of tools and a range of data handling models, which include multivariate statistical analysis, time series analysis, graphical analysis, and other data science approaches. As seen in Figure 8, multifunctional, multi-angle, and deep-level processing, analysis, prediction, mining, and statistical data visualization support economic operations and societal advancement by providing analysis and decision help.

IoT big data analysis visualizations can be given to IoT users in a highly intuitive manner, simplifying the extraction of vital knowledge and supporting users in making the most informed decisions possible. The deployment of IoT has a direct impact on the national economy, countless people's lives, and the timeliness of life safety, all of which place a premium on the timeliness, reliability, and authenticity of DM findings. Experts in big data and industry should examine the DM algorithm. For IoT applications, predictive analytics is crucial. It is vital to establish a research team of industry experts, IoT specialists, and big data experts to examine prediction models and algorithms that adapt to IoT big data across several sectors. Networking necessitates the development of a new set of theories and methods for standardizing and flexibly organizing diverse geographically dispersed data resources in such a way that users can easily search for keywords, tag keywords, or other input semantics, thereby increasing their ability to derive knowledge actively. Aggregation of raw data acquired by many sensors, aggregation of multidimensional data, collaborative sensing among various users, and data quality management all contribute to the accuracy of processed findings, which is the primary objective of IoT big data research.

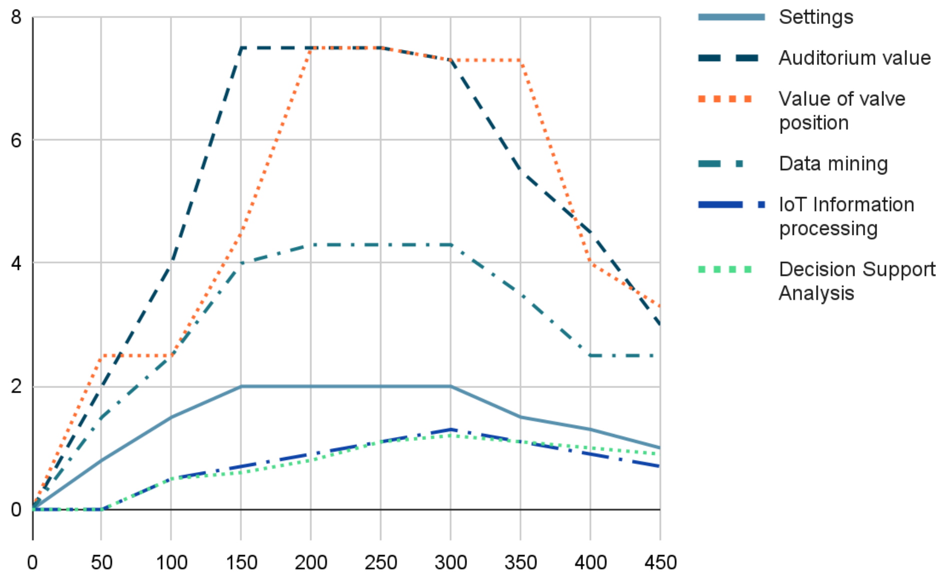

Fig. 8. Analysis of decision support information forth result

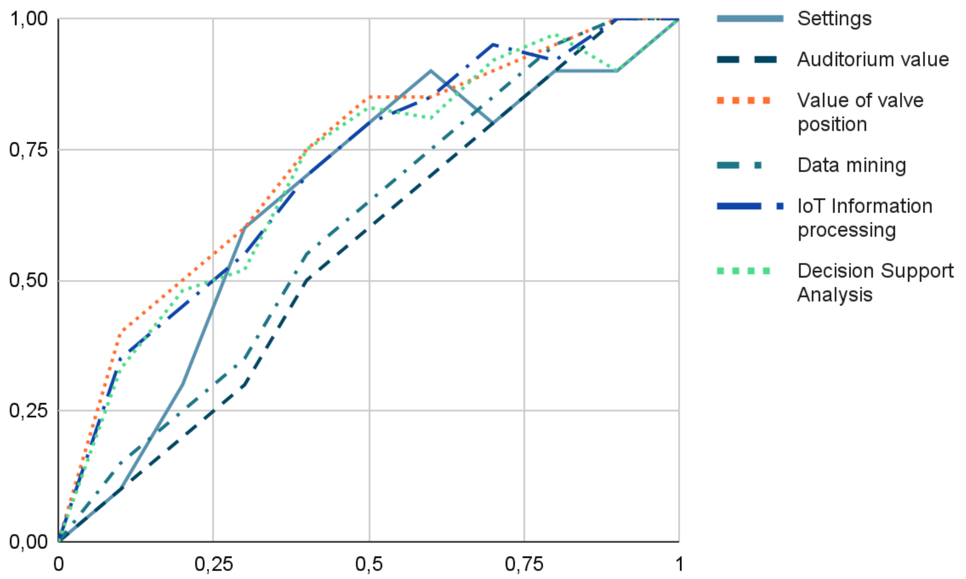

Fig. 9. Analysis of informed decision support fifth result

4.2. DSS analysis under DM

Frequently, the data in a data warehouse is derived using a range of different data collection techniques. To ensure that this data is correct, consistent, and efficiently queryable, it must be cleansed and regulated using data warehouse technologies. In comparison to database technology applications, data warehouse is more of a process for integrating and analyzing data spread throughout an organization than it is a commercially available product. Appropriate reduction and adjustment methods, such as information decision support analysis (6), are necessary for individual DW systems with diverse requirements, processes, and business scales. As seen above, data analysis may take the shape of periodic reports, statistical charts, theme-based inquiries, multi-dimensional analysis, in-depth research, and forecasts. If the transaction database is left alone but the min-supp and min-conf values are altered, the user must gradually modify the two min-supp and min-conf thresholds in order to concentrate on the actually useful association rules, which is a dynamic interaction process. If the minimum-supply value changes, some of the original FIS may lose it while others gain it, as the DSS data analysis indicates in Figure 11.

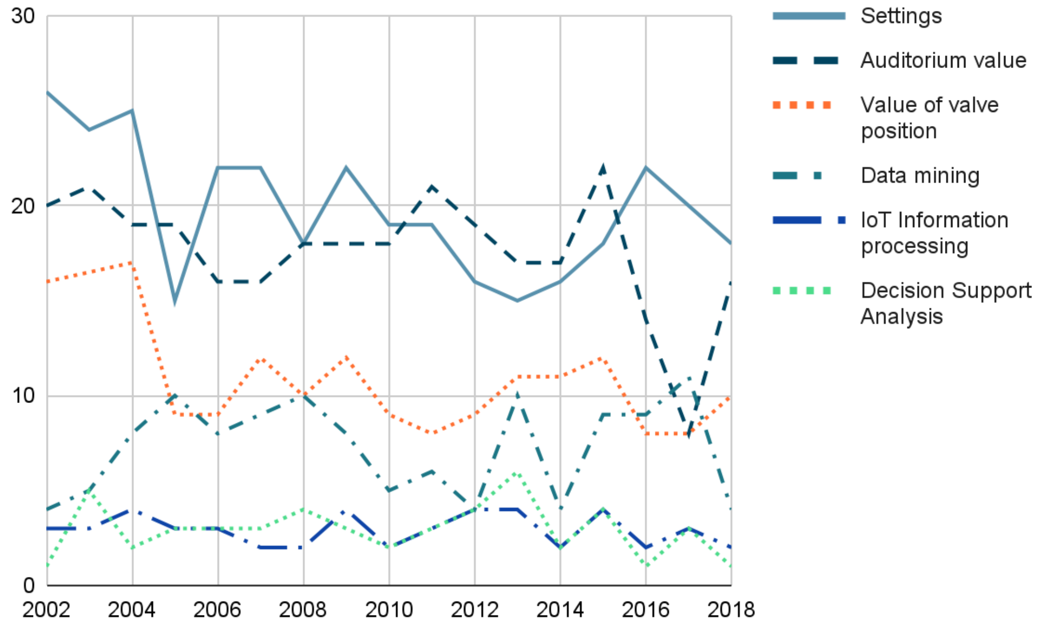

Fig. 10. Analysis of informed decision support sixth result

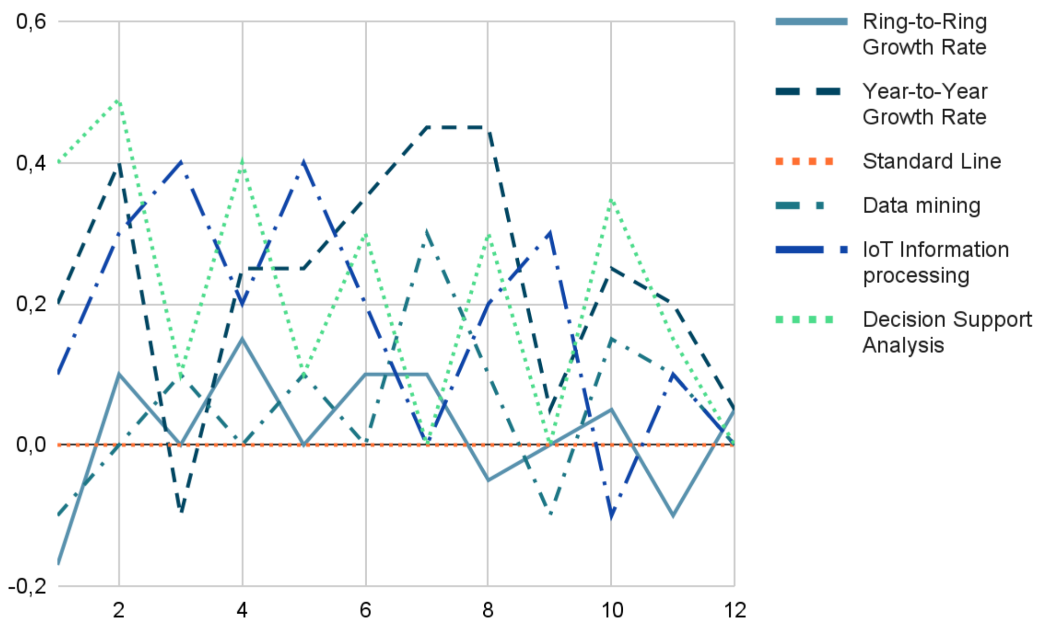

Fig. 11. Analysis of income data by DSS.

With the advancement of Internet technology and software development structures, the currently popular Browser/Server (B/S) structure and three-layer client/server architecture may provide an excellent foundation for CMS development, making it the optimum choice. The ".net" development environment was used for the background program in order to implement the B/S structure. As a result, current resources can be efficiently leveraged and applied to the CMS to meet the needs of varied scales. The technical aspect is divided into three components: the development of a portal for statistical analysis support, textual information retrieval, and data input and collection. The process formulation is depicted in Figure 12 of the DSS technical analysis.

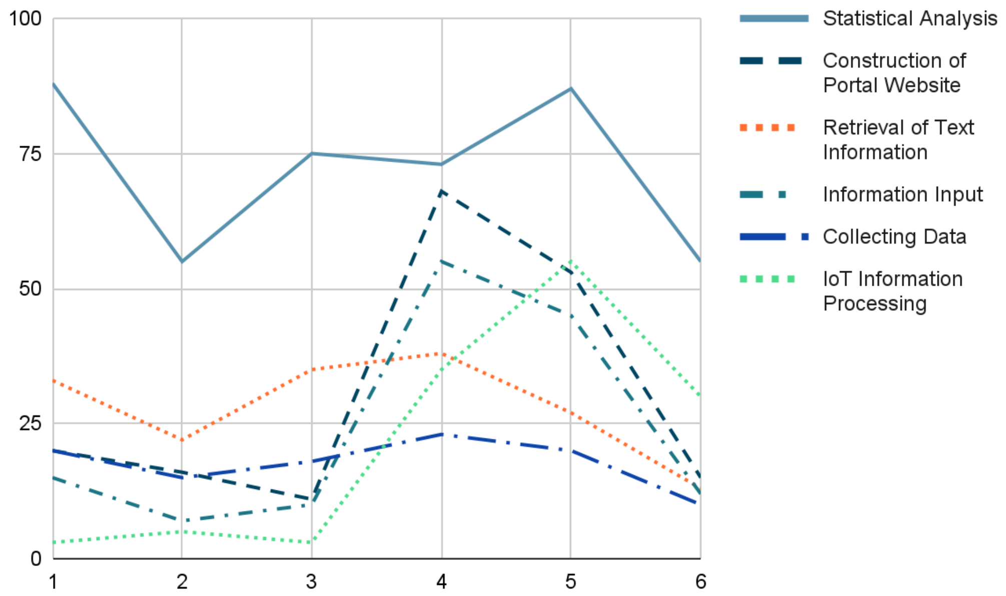

Fig. 12. DSS technical analysis.

Implementing a data warehouse system is a continuous cycle process that necessitates ongoing development. When a business officer increases the value of the company by utilizing the DW, further comprehensive and summary data will be sought for examination. Additionally, data warehouse administrators must evaluate their data warehouses' capacity and performance requirements. It is capable of discovering, among other sorts of knowledge, general knowledge, differential knowledge, and predictive knowledge. Furthermore, it is capable of performing highly automated data analysis, induction and reasoning, as well as projecting future patterns and behavior. As a result, users gain a better understanding of the underlying value of data and are able to give consumers more informed decision support. Predictive analysis mining may forecast the outcome based on the value of a data item, resulting in a known precise value. Parametric data mining is the process of describing the rules that govern the data or organizing the data according to their similarity; nevertheless, it cannot be used directly for forecasting.

By merging Data warehouse, intelligent analysis, and data mining techniques to obtain intelligent business data processing, it is necessary to detect and comprise hidden knowledge, create enterprise-level industry analysis and DSS, as well as provide quick and correct scientific decision-making for market operations, thus also trying to establish a strong DSS system for analysis and enabling top-down analysis, management, and predictive modeling all across entire scope of the market.

5. Conclusion

To acquire a complete understanding of the decision information system for intelligent manufacturing data processing provided by the Internet of Things, it is necessary to conduct extensive research on DM technology. DM technology has the ability to supply decision makers with crucial knowledge or information, in addition to significant economic benefit. Additionally, an IoT-based intelligent manufacturing IoT-based DM model for DSS information processing is provided. Numerous frequently encountered DM algorithms are investigated, including ARS and AA. The algorithm for mining DTs is explored, as is the technique for generating multiple DTs and the mechanism for DT pruning. Additionally, an enterprise-level data processing DSS for intelligent IoT is created and deployed, with its functional needs examined. The implementation technology, general design, including system structural and database design, as well as functional modules, are defined and designed, assisting enterprises in realizing intelligent manufacturing IoT information processing DSS. However, due to time and resource constraints, research on IoT intelligent manufacturing DSS information processing for enterprises is not yet complete, and numerous aspects need to be improved. For instance, DM technology could be further investigated to demonstrate the intelligence of DSS.

Using the data warehouse, intelligent analysis, and data mining techniques to improve intelligent business information processing empowers the exploration and containment of hidden information, the establishment of enterprise-level business analysis and decision support systems, and the provision of timely and accurate scientific decision-making for market operations, thereby establishing a powerful DSS platform for operational analysis, the realization of top-down analysis, and the provision of timely and accurate scientific decision-making for market operations.

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