Construction of Industrial Product Lifecycle Management System Based on CAD

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Abstract. In the stage of product design, the information exchange between various departments is often opaque, which leads to some problems in product design that cannot be found and solved in time. Computer aided design (CAD) technology is widely used in industrial product design. However, how to effectively manage and use these CAD data is still an urgent problem to be solved. This article studies the construction of Product Lifecycle Management (PLM) system using CAD. The results show that the proposed PLM system based on CAD technology has obvious advantages and potential in PLM, and can realize more efficient product design, optimization and management. By introducing CAD technology and optimizing PLM system, it is helpful to promote the growth of related fields and provide effective technical support for enterprises to save costs and improve efficiency.

Keywords: Product Lifecycle Management; CAD; Product Design
DOI: https://doi.org/10.14733/cadaps.2024.S13.75-91

1 INTRODUCTION

Due to the rapid growth of global economy, the design and manufacture of industrial products has become an important part of national technological competition. However, the traditional PLM method faces many challenges. In the traditional PLM system, all kinds of data and information involved in the product design stage are often scattered in different systems and departments. The Sustainable Network Physical Production System (SNCPS), as an important component of the smart city economy, has attracted widespread attention. SNCPS achieves a new production model by combining physical entities (such as devices, products, etc.) with virtual entities (such as data, information, etc.). Andronie et al. [1] conducted a systematic literature review on sustainable network physical production systems in the big data-driven smart city economy. SNCPS is widely used in urban economy, such as intelligent manufacturing, urban logistics, waste treatment, etc. Among them, the field of intelligent manufacturing is an important application field of SNCPS. Through SNCPS, the automation, informatization, and intelligence of the production process can be achieved, improving production efficiency and product quality. In the field of urban logistics, SNCPS can achieve real-time sharing of logistics information, optimize logistics paths, and reduce logistics costs. In the field of waste treatment, SNCPS can achieve the classification, recycling, and treatment of waste, which is conducive to resource recycling and environmental protection. These data include product design data, process planning data, manufacturing data and product use data. Due to the dispersion of these data, PLM system cannot effectively manage and utilize these data in a unified way, thus affecting the efficiency of product design and the improvement of product quality. Immersive virtual reality technology has rapidly developed globally. More and more universities and educational institutions are attempting to introduce VR technology into the classroom to improve teaching quality and effectiveness. In industrial design education, the application of VR technology has also achieved some results, such as virtual prototype production and product simulation. In the future, with the continuous improvement and popularization of VR technology, immersive virtual reality education will become more mature and diverse, including more realistic scenes, more interactive links, and higher teaching quality. Industrial design education aims to cultivate students' design thinking, practical ability, and innovative spirit to adapt to the constantly developing manufacturing industry and social needs. Traditional education methods often focus on theoretical teaching and static presentation, which cannot meet the practical needs of modern industrial design. Therefore, it is imperative to adopt new educational technologies and methods. Immersive virtual reality technology, with its unique interactivity and immersion, provides infinite possibilities for industrial design education [2]. In addition, the traditional PLM system still has the problems of opaque information and inconsistent design process. In the stage of product design, the information exchange between various departments is often opaque, which leads to some problems in the stage of product design that cannot be found and solved in time. Differential algebraic equations are a hybrid system composed of algebraic equations and differential equations, widely used in various fields such as engineering, physics, biology, etc. However, due to the complexity of its mathematical structure, solving differential algebraic equations often has numerical infeasibility, which brings difficulties to practical applications. Therefore, finding an effective numerical solution method, especially for differential algebraic equations with numerical infeasibility, has important practical significance. Beykal et al. [3] designed a data-driven optimization algorithm that utilizes the characteristics and laws of historical data to optimize the solving process of differential algebraic equations, improving solution efficiency and stability. Intelligent manufacturing refers to a manufacturing model that continuously introduces advanced technologies and concepts, improves manufacturing efficiency, optimizes resource allocation, and achieves industrial upgrading. Data driven product design refers to the process of optimizing product design and improving product performance using a large amount of data, statistical analysis, machine learning, and other technologies. The combination of the two can not only enhance the competitiveness of the manufacturing industry, but also achieve sustainable development. Therefore, data-driven product design for intelligent manufacturing has become a hot research topic today. Feng et al. [4] used methods such as review, case analysis, and systematic analysis to analyze historical literature. Conduct comprehensive and in-depth research on data-driven product design for intelligent manufacturing. Finally, using the system analysis method, propose optimization strategies and suggestions for data-driven product design for intelligent manufacturing. Moreover, due to the inconsistency between the design processes of various departments, the product design stage is not smooth and inefficient. The residual generator based on parity relationship is a common diagnostic tool. The parity relationship residual generator detects whether there are anomalies or faults in the signal by extracting and comparing the parity features of the signal. In order to improve detection accuracy and efficiency, Jiang et al. [5] proposed an optimized design scheme. Firstly, focus on selecting appropriate parity relationships to better characterize the characteristics of the signal. The polynomial parity analysis method was used to represent the signal as a series of polynomials and calculate its parity characteristics. Secondly, by analyzing residual information, i.e. the difference between the signal and the model, anomalies or faults are detected. To this end, we have established a highly adaptable statistical model to describe the random characteristics of signals and use residual information to diagnose faults. Finally, we optimized the parameters of the generator to reduce computational complexity and improve detection speed. CAD technology is widely used in industrial product design. How to effectively manage and use these CAD data is still an urgent problem to be solved.

This article puts forward a method of PLM system construction based on data mining (DM). This method integrates product design data, process planning data, manufacturing data and product use data scattered in various systems and departments into a unified data management platform through data integration technology. Using DM technology, valuable information and knowledge are extracted from the integrated data, and these information and knowledge are classified, analyzed and summarized; Through information visualization technology, the information and knowledge obtained by DM are displayed in the form of graphics, images and animations, so that users can understand and master all kinds of data and information in the product design stage. Using knowledge management technology, the information and knowledge obtained by DM are sorted and summarized, and a knowledge base is formed. With the rapid development of the global economy, the manufacturing industry, as an important pillar of the national economy, has become the focus of attention for its optimization, upgrading, and high-quality development. The application of intelligent structured data in the manufacturing industry is changing our understanding and practice of manufacturing optimization. Khan et al. [6] delved into the integration of data-driven process reengineering and process interdependence in manufacturing optimization supported by intelligent structured data, with the aim of revealing its inherent mechanisms and application value. Intelligent structured data refers to information generated during the production process that has a certain structure, clear semantics, and is associated with other data. Through deep mining and analysis of data, we can more accurately understand the bottlenecks in the production process, improve production efficiency, reduce costs, and improve product quality. Data driven process reengineering refers to the optimization and redesign of production processes by collecting and analyzing data from the manufacturing process.

Liu [7] introduced the rapid industrial product design method and its application based on 3D CAD system. This method achieves rapid industrial product design through steps such as requirement analysis, design scheme, modeling, and rendering. Through case analysis, it has been proven that this method can improve design efficiency and shorten product development cycle, and has important application value. Looking forward to the future, with the continuous development of computer technology, rapid industrial product design methods based on 3D CAD systems will have more application scenarios and optimization space. Meanwhile, with the integration and application of technologies such as artificial intelligence and big data, this method will become more intelligent and automated, bringing more innovation and development to industrial product design. The research content is not only of great significance to PLM, but also reflects important significance in improving the core competitiveness of enterprises. Through data integration and DM technology, problems and trends in product design stage can be found in time, so as to be corrected and optimized in time. This not only improves the design efficiency and quality of enterprises, but also reduces the cost of product research and development. The data management method based on product morphology is a data management model for product morphology. Liu et al. [8] combined relevant theories and methods of product morphology, computer science, and data management technology to efficiently collect, store, analyze, and mine data from various stages of the product lifecycle. The data management method based on product morphology is a data management model for product morphology. It combines relevant theories and methods of product morphology, computer science, and data management technology to efficiently collect, store, analyze, and mine data from various stages of the product lifecycle. The data management method based on product morphology is a data management model for product morphology. It combines relevant theories and methods of product morphology, computer science, and data management technology to efficiently collect, store, analyze, and mine data from various stages of the product lifecycle. Nguyen et al. [9] proposed a 3D printing process optimization strategy based on data-driven machine learning method. This method can extract key factors from a large amount of data, establish predictive models, and improve printing speed and accuracy. In the data collection stage, we first determined the factors related to the 3D printing process through experimental design, including printing temperature, printing speed, filling density, etc. Then, we used an online monitoring system to collect a large amount of data in real-time during the 3D printing process. In order to ensure the accuracy of the data, we conducted a series of preprocessing, such as filtering, denoising, etc. In the data-driven machine learning stage, we used algorithms such as random forest and support vector machine to analyze and model the collected data. These algorithms can extract the most critical factors that affect the 3D printing process from a large amount of data, and establish predictive models to predict printing speed and accuracy. Through information visualization and knowledge management technology, enterprises can better understand the market demand, grasp the dynamics of competitors and master their own competitive advantages. The research has the following innovations:

⊖ This article proposes a method of combining DM technology with CAD technology, which integrates product design data, process planning data, production manufacturing data, and product usage data dispersed in various systems and departments into a unified data management platform through data integration technology.

⊜ Through information visualization technology, the information and knowledge obtained by DM are presented in the form of graphics, images, and animations, in order to facilitate users' understanding and mastery of various data and information in the product design stage.

⊛ A PLM system based on DM is established, which realizes the unified management and monitoring of the whole stage of product design, manufacture and use.

The first part is the introduction, which introduces the research significance and methods, and puts forward the main research contents and innovations; The second section is an overview of related technologies, introducing the related concepts of CAD technology and DM technology, and analyzing the application of these two technologies in PLM; The third section analyzes the requirements of PLM system and expounds the technical implementation scheme of the system; The fourth section is the realization and application of the system, which introduces the realization stage of the system; The fifth section is system assessment and optimization; The sixth section is the summary and prospect, summarizing the main research achievements and contributions, analyzing the limitations of the research and the needs of future research.

2 OVERVIEW OF RELATED TECHNOLOGIES

With the continuous development of system metabolic engineering and machine learning technology, data-driven metabolic engineering will have more widespread applications. By continuously improving the comprehensive understanding and understanding of biological systems, more and more new methods and technologies will be applied to system metabolic engineering, further promoting the optimization of biological processes and the development of biological products. With the continuous progress of machine learning technology, more efficient and accurate algorithms and models will emerge, further improving the predictive ability and optimization effect of data-driven metabolic engineering. Presnell and Alper [10] optimize biological processes and develop biological products through comprehensive and systematic analysis and simulation of biological systems. System metabolic engineering reveals the internal mechanisms of biological processes by studying the overall structure and function of biological systems, providing theoretical basis and practical guidance for the optimization of biological processes. Saura et al. [11] reviewed the current research status of digital marketing in small and medium-sized enterprises through data-driven strategies by reviewing and evaluating relevant literature. Research has found that digital marketing has broad application prospects in small and medium-sized enterprises, but there are also some problems and challenges. Specifically manifested in data-driven marketing strategies, digital marketing channels, and evaluation of digital marketing effectiveness. Digital channels such as social media, search engines, and email play an important role in digital marketing. However, small and medium-sized enterprises often have the problem of improper use in practical applications. For example, some companies overly rely on certain digital channels while neglecting the role of other channels; Some companies lack coordination between different channels, resulting in poor marketing effectiveness. Therefore, how to reasonably use and coordinate different digital channels to improve brand awareness and customer loyalty is a problem that small and medium-sized enterprises need to pay attention to. The application of structured data storage in bioprinting can significantly improve the efficiency and quality of data management in the bioprinting process. By selecting appropriate data types, designing reasonable storage formats, and developing comprehensive data backup strategies, bioprinting data can be effectively protected and managed. In addition, through data indexing and query optimization, data analysis and mining, as well as data visualization and interactive interface design, in-depth analysis and optimization of bioprinting data can be carried out to further improve the quality of bioprinting. With the continuous development of bioprinting technology, structured data storage has broad application prospects in the future bioprinting field. Schmieg et al. [12] utilized data analysis techniques to extract valuable information from massive bioprinting data, such as optimal cell culture conditions and material performance. This requires in-depth data mining and analysis to provide support for the optimization of bioprinting. With the continuous development of technology, computer-aided design (CAD) has been widely applied in many fields. In the process of product design and manufacturing, computer-aided intelligent assembly modeling (CAI) has become an important tool that can help engineers and designers better understand and capture the design intent of products. Mo et al. [13] explored product information modeling for capturing design intent in computer-aided intelligent assembly modeling. In computer-aided intelligent assembly modeling, capturing product information modeling of design intent is crucial. Semantic modeling method is a method of using natural language to describe product information. It can help designers better capture the semantic information of products, such as their functions, usage scenarios, etc.

With the rapid development of intelligent manufacturing technology, product optimization has become an important means to improve the competitiveness of enterprises. Simulated data-driven design, as an emerging method, can quickly and effectively achieve product optimization. Shao et al. [14] introduced a simulated data-driven design method for rapid product optimization, aimed at improving product quality, reducing costs, and meeting customer needs. Simulated data-driven design is a technology based on computer simulation and data science, which predicts and optimizes product performance by establishing digital models of product performance. This method has the advantages of shortening product development cycles, reducing research and development costs, and improving product quality, and has become a research hotspot in the field of intelligent manufacturing. By simulating data-driven design models, predict product performance for different design schemes and select the best solution. In addition, the design scheme can also be optimized to improve product performance. Simulating data-driven design models can identify factors that affect product quality, and take effective control measures to achieve continuous improvement of product quality. In intelligent manufacturing, data-driven product design has become an important research direction, which can enable enterprises to better meet customer needs, optimize production processes, and improve market competitiveness. Suryadi and Kim [15] proposed a data-driven method for constructing customer selection sets using online data and customer reviews. Optimize product design by simulating customer selection sets. Present the optimized product design plan to customers, collect feedback from customers, and further optimize the product design plan to achieve a product design that better meets customer needs. Using machine learning algorithms to establish a customer selection set model, integrating customer needs and preferences into product design. Finally, the product design is optimized by simulating a customer selection set to achieve a product design that better meets customer needs. With the rapid development of big data and artificial intelligence technology, the application of product specification recommendation optimization integrated data drivers in various industries is becoming increasingly widespread. Wang et al. [16] introduced how to use LDA-LightGBM and QFD product specifications to recommend and optimize integrated data drivers, aiming to improve product quality and customer satisfaction. LDA LightGBM is a distributed document topic model based on the LightGBM algorithm. Divide customer requirements into different levels and sub requirements, and use a matrix to associate customer requirements with product characteristics, design parameters, etc. By calculating the weighting matrix and similarity matrix, QFD can determine the degree of impact of each design parameter on customer needs, thereby providing a basis for product specification recommendation and optimization. Establish an association matrix between customer needs and product design parameters in the House of Quality for quantitative analysis of the impact of each design parameter on customer needs.

Data driven design space exploration and development is a design method based on big data and artificial intelligence technology. It collects a large amount of additive manufacturing design data, establishes a database, and utilizes advanced algorithms for data analysis and mining. In this process, data-driven design can provide powerful support, including design ideas, optimization suggestions, and even direct generation of design solutions. Xiong et al. [17] conducted in-depth analysis on the design data of a large number of aviation engine components to identify key factors affecting performance, optimize design plans, and improve engine performance and reliability. The exploration and development of data-driven design space for additive manufacturing design is an innovative design method with great potential and development prospects. It automates the exploration and development of design space through big data and artificial intelligence technology, improves design efficiency and accuracy, and achieves more complex product design. Through practical application cases, it can be seen that data-driven design methods can not only optimize the performance and reliability of products. With the continuous development of enterprise business, software requirements are becoming increasingly complex. How to choose software that is suitable for one's own business processes has become an important issue faced by enterprises. Zancul et al. [18] explored how to make software selection based on the Business Process Reference Model (BPRM) by introducing it, and illustrated it with an example of Product Lifecycle Management (PLM). According to the process modeling phase of BPRM, enterprises need to clarify their own business processes and their interrelationships. When choosing software, the first thing to pay attention to is whether its functionality matches the actual business needs of the enterprise. For example, product lifecycle management software should have management functions for various stages, including product planning, development, launch, and maintenance. In addition to functional compatibility, software performance and stability are also crucial. Efficient software can enhance enterprise business processing capabilities and reduce resource consumption. Meanwhile, software with good stability can reduce the risk of system failures and ensure the continuity of enterprise business. In the data preparation stage, it is necessary to clarify the data source, data type, and processing method. For product specification data, it can be obtained through methods such as product lifecycle management tools, market research, or documentation, and organized into compliant data tables. Obtain product prototype data, production process data, and customer feedback data from product lifecycle management tools. Obtain information on competitors' product specifications, prices, and market share from market research. Obtain historical sales data, failure rates, maintenance records, and other related information of the product from document records. Zhang et al. [19] adjusted product specifications to adapt to market changes by predicting market demand trends for different product specifications. At the same time, comprehensively consider the budget constraints and competitive environment of the enterprise to determine the optimal product specification optimization plan. Prioritize optimizing the important specification attributes of best-selling products within the allowable cost range to improve product quality and customer satisfaction.

3 SYSTEM REQUIREMENTS ANALYSIS AND DESIGN

CAD technology is a tool for product design and development by computer. CAD technology can digitize the traditional product design stage and help designers to carry out tasks such as 3D modeling, simulation and optimization of products, thus speeding up the stage of product design and development. In PLM, CAD technology can be used in all stages of product design, manufacturing, assembly and maintenance.

By establishing the 3D model of the product with CAD software, designers can carry out visual design and simulation, so as to better understand the characteristics of the product such as shape, structure and function. Moreover, the 3D model can also be used in the subsequent processing and assembly process to improve production efficiency and quality. Using the parametric function of CAD software, designers can modify and optimize the product model according to their needs. By adjusting the parameters of the model, mass production and customized design can be conveniently carried out to meet the needs of different customers. Through the simulation function of CAD software, designers can simulate and test the performance of products before manufacturing. This can help designers find and solve potential problems and improve the quality and reliability of products. Moreover, simulation can also optimize the design scheme and reduce the cost of product development. CAD software usually integrates data management function, and designers can manage and maintain product data conveniently. This can ensure the consistency and integrity of data and improve the design efficiency and quality.

In PLM, DM technology can help enterprises to mine valuable information and knowledge from massive data, thus supporting enterprise decision-making and optimization.

Through clustering analysis algorithm, similar product data are grouped into one category. This can help enterprises discover the distribution and characteristics of product data and classify and manage different product categories. Association rule mining algorithm can help enterprises find the correlation between product data. Through the analysis of product data, we can find the correlation and mutual influence between different products, thus supporting the product combination and optimization of enterprises. Through the classification analysis algorithm, the product data are classified according to certain characteristics. This can help enterprises find the differences and characteristics between different categories, so as to formulate more detailed product strategies and management methods. Time series analysis algorithm can help enterprises find the laws and trends of product data changing with time. This can help enterprises predict the future market demand and changing trend, so as to make market layout and countermeasures in advance.

In the life cycle of industrial products, CAD technology provides strong support for product design. Through these technologies, designers can create high-quality 3D models for simulation and analysis, so as to better understand the functions and performance of products. With the help of CAD technology, manufacturers can simulate and optimize the production process. This helps to determine the best production strategy, reduce waste in production and improve efficiency.

Through DM technology, enterprises can use historical sales data to forecast the market. This can help enterprises to understand the market demand and consumer behavior, so as to formulate more accurate market strategies.

Through the mining and analysis of production data, enterprises can find product quality problems and take corresponding improvement measures. In the later period of product life cycle, DM technology can help enterprises understand the usage and maintenance requirements of products. Combining CAD technology and DM3. technology, enterprises can better understand the market demand and competitive situation, thus promoting product innovation and development. By applying CAD technology and DM technology, enterprises can optimize production processes, improve production efficiency and reduce costs. Moreover, enterprises can better predict market demand and adjust supply chain strategies accordingly, which is helpful to reduce inventory costs and improve operational efficiency. In the previous chapter, the application of CAD and DM technology in PLM is discussed. These technologies provide enterprises with the ability to improve product design, optimize production processes, and enhance market forecasting and decision support. In order to give full play to the potential of these technologies, it is needed to analyze and design the system in detail.

3.1 PLM System Requirements Analysis

(1) demand overview

PLM system requirements include the following aspects:

㊀ Design: Support 3D modeling, parametric design, simulation and other tasks of products.

㊁ Production: mass production and customized production are supported to meet the requirements of optimization and improvement of production processes.

㊂ Market: Support functions such as market forecast and sales strategy formulation to help enterprises better understand market demand and competitive situation.

④ Data management: ensure data consistency, integrity and security, and support DM and analysis.

(2) Demand refinement and analysis

In order to meet the above requirements, the system needs to be further refined and analyzed, including the following aspects:

㊀ Functional modules of the system: according to the requirements, the system is divided into different functional modules, such as 3D modeling module, parametric design module, simulation module, market forecasting module, etc. Each module has its own specific input, processing and output.

㊁ Data flow: determine the data flow of the system, including data input, processing and output, as well as the relationship and flow direction between data.

㊂ Performance requirements: Set performance indicators for each functional module, such as processing time and accuracy, to meet the response speed and data processing capacity requirements of the system.

④ Security requirements: In order to protect the core data and intellectual property rights of enterprises, strict security measures need to be set, including data encryption, access control, intrusion detection, etc.

3.2 PLM System Design

(1) System architecture design

According to the results of demand analysis, the system architecture can be designed. The architecture should include the following levels:

㊀ Data layer: This layer includes database and file system, which is used to store the original data and calculation results of the system.

㊁ Calculation layer: This layer includes various algorithms and models, which are used to process and analyze the data in the data layer.

㊂ Application layer: This layer includes various application programs, which are used to provide a user interface, process user's requests and return results.

(2) Functional module design

According to the requirements refinement and analysis results, each functional module of the system can be designed. Each module has its own specific input, processing, output and corresponding data flow. The following are some major functional modules:

㊀ 3D modeling module: This module can accept 2D sketches and other parameters input by designers to generate 3D models.

㊁ Parametric design module: This module can automatically adjust the size and shape of products according to the parameters input by designers to support mass production and customized design.

㊂ Simulation module: This module can simulate the 3D model and simulate the performance of the product, so that problems can be found and improved before manufacturing.

④ Market forecasting module: This module can use DM technology to analyze historical sales data and market trends, and predict future market demand, thus making more accurate market strategies for enterprises.

4 SYSTEM IMPLEMENTATION AND APPLICATION

4.1 System Algorithm Implementation

3D modeling algorithm is one of the core algorithms of PLM system. The algorithm can accept 2D sketches and other parameters input by designers and automatically generate 3D models. Firstly, 2D sketches and other parameters are input on the user interface. The system uses sketch recognition algorithm to recognize 2D sketches and convert them into 3D models. The system checks the quality of the 3D model, such as whether it meets the design requirements; If it meets the requirements, the 3D model will be saved in the database, otherwise the designer will be prompted to modify it. The data classification steps are shown in Figure 1.

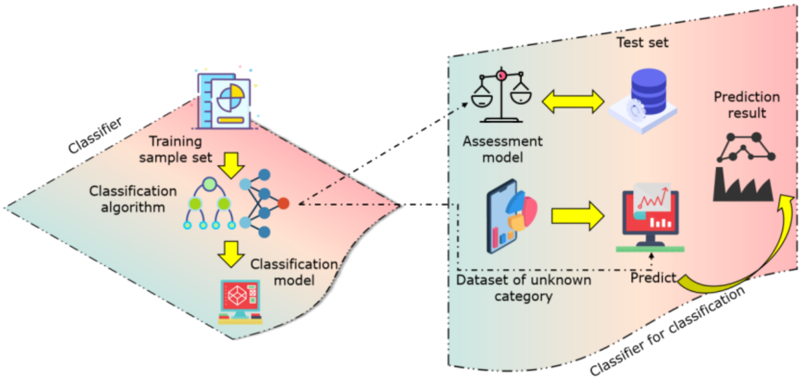

Figure 1: Steps of classification.

Let S set have s sample data and s class attributes with different values: $C_i(i=1,2,\cdots,m)$. Assuming that the quantity of samples in class C_i is s_j, the total information entropy for this sample is:

$$I(s_1,s_2,\cdots,s_m)=-P_i\log_2(P_i) \tag{1}$$

So, for a subset f that has been given now, calculate its expected value as:

$$I(f_{1j},f_{2j},\cdots,f_{mj})=-\sum_{j=1}^{n}P_i\log_2(P_{ij}) \tag{2}$$

Now suppose that the coordination degree of a decision-making system such as $S=(U,C\cup D,V,f)$, then $X\to D$, can be expressed as $CON(X\to D)$, then the decision-making coordination degree is:

$$CON(X\to D)=|X\cup D|/|X| \tag{3}$$

Where $|X|=IND(X)$ represents the cardinal quantity of $IND(X)\subseteq U\times U$.

The simulation algorithm can simulate the 3D model and simulate the performance of the product, so as to find problems and improve them before manufacturing. Designers select simulation parameters and simulation conditions on the user interface; The system uses the simulation algorithm to simulate the 3D model and get the corresponding simulation results. Designers analyze and evaluate the simulation results, find problems and make improvements; If it meets the requirements, the simulation results will be saved in the database, otherwise the designer will be prompted to modify it. The data warehouse structure of the system is shown in Figure 2.

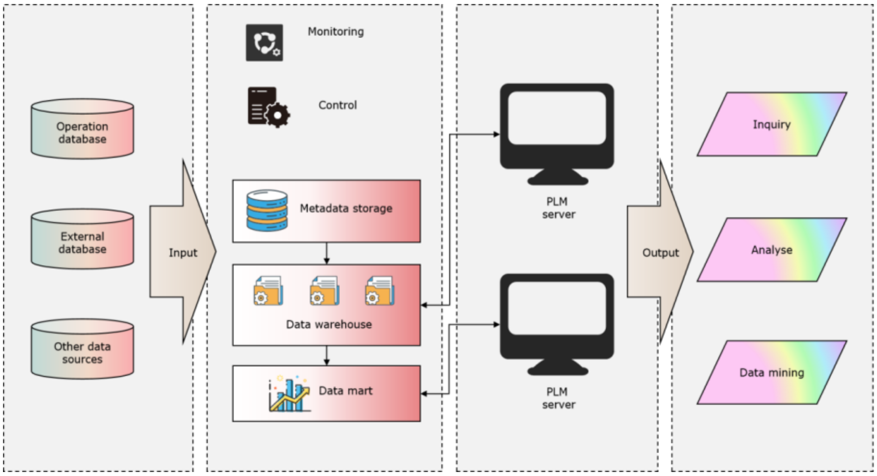

Figure 2: Data warehouse structure of the system.

Assuming that the sampling sample value of data clustering features is $S = \overline{X_1}, \cdots, \overline{X_k}$, the related directional features distributed in the time interval $T_1, \cdots, T_k$ are as follows:

$$\rho_{XY} = \frac{\operatorname{cov}(X,Y)}{\sqrt{D(X)}\sqrt{D(Y)}} \tag{4}$$

X,Y classifies attribute sets for data stream micro-clusters.

The maximum entropy of data is an effective feature that signals contain useful information saturation, which can effectively reflect the feature information of audio and video data in the database. Thus, the feature information flow in database access is:

$$WT_f(\alpha,\tau) = \frac{1}{\sqrt{\alpha}} \int x(t)\psi^*\left(\frac{t-\tau}{\alpha}\right)dt \tag{5}$$

Among them, the information flow characteristics of database access are related to two parameters α, τ.

Compared with other dimensions, one dimension of multi-dimensional data is different not only in its different attribute meanings, but also in its different contribution to the degree of separation between classes. It is needed to introduce a balance coefficient λ_i, through which the contribution of each dimension feature can be balanced λ_i. The calculation formula is as follows:

$$\lambda_i = \frac{\max\left\{\sum_{i=1}^{k} c_{il}, l = 1,2,\cdots,s\right\}}{\sum_{i=1}^{k} c_{ij}}, \; j = 1,2,\cdots,s \tag{6}$$

Where k is the quantity of clusters; c_{il} is the calculated cluster center matrix.

It is advisable to use the standard deviation of the distance center matrix to describe the degree of separation:

$$Cdist = \sqrt{\sum_{i=1}^{k}\left(c_{ij} - \overline{c_j}\right)^2},\ j = 1,2,\cdots,s \tag{7}$$

DM algorithm can help enterprises to mine valuable information and knowledge from massive data, and support enterprise decision-making and optimization. In PLM system, DM algorithm can analyze production data and sales data, and provide decision support for enterprises. Firstly, the data to be mined is extracted from the database, and preprocessing operations such as cleaning and conversion are carried out. Then clear the specific problems that need to be solved, such as forecasting sales and analyzing customer behavior; Select the appropriate DM algorithm according to the target; The selected mining algorithm is used to deeply analyze and explore the data, and the hidden patterns and laws are found. Finally, the mining results are assessed, interpreted and applied, and the mining results are presented in a visual way for users to understand and use.

$f(x)$ is the frequency distribution of data attribute in a specific universe. According to the real distribution of, the accumulation of many cloud $C(Ex_i, En_i, He_i)$ is generated adaptively, and its mathematical expression is:

$$f(x) \rightarrow \sum_{i=1}^{n}\left(a_i * C(Ex_i, En_i, He_i)\right) \tag{8}$$

Where a_i is the amplitude coefficient; n is the quantity of discrete concepts generated after transformation.

Create a matrix O of $N \times N$, and O_{ij} represents the quantity of samples with actual grade i and predicted grade j. The weight matrix is also a matrix w of $N \times N$, and the calculation formula is:

$$w_{ij} = \frac{(i-j)^2}{(N-1)^2} \tag{9}$$

Determine the correct quantity of clusters. Take Sum of squares of errors(SSE) as a function to measure the clustering quality:

$$SSE = \sum_{i=1}^{k}\sum_{x \in C_i} dist(c_i, x)^2 \tag{10}$$

The distance $d(p,C)$ between the object p and the cluster C is defined as the distance between p and the abstract of the cluster C, which is expressed as:

$$d(p,C) = \frac{d_C + d_N}{m} \tag{11}$$

4.2 System Application

(1) Product development stage

In the product development stage, designers can use 3D modeling algorithm to design products. Through 3D modeling technology, designers can build 3D models of products on computers and conduct simulation tests. This can improve the design quality and reliability of products, and avoid the situation that problems need to be redesigned only after design. Moreover, designers can also use parametric design algorithms to customize products and mass production to meet the different needs of the market.

(2) Product production stage

In the product production stage, PLM system can help enterprises realize automatic production. Through parametric design technology, enterprises can quickly adjust and optimize production parameters and realize mass production and customized production. Moreover, simulation technology can help enterprises find and solve potential problems before manufacturing, and reduce production costs and risks. DM technology can analyze production data, help enterprises optimize production processes and improve production efficiency. By mining the data in the production stage, enterprises can find the hidden problems and improvement points, thus continuously optimizing the production process and improving the production efficiency and product quality.

(3) Product sales stage

In the product sales stage, PLM system can help enterprises to make sales forecast and market strategy formulation. Through DM technology, enterprises can analyze historical sales data, understand market demand and consumer behavior, and thus formulate more accurate market strategies. Moreover, simulation technology can help enterprises predict the sales trend of products and provide support for enterprises to make more accurate production plans. Through the prediction of market trends and the formulation of market strategies, enterprises can better meet market demand and improve sales performance.

5 SYSTEM ASSESSMENT AND OPTIMIZATION

The main purpose of the experiment is to verify the feasibility and effectiveness of DM algorithm in the construction of CAD industrial product life cycle management system. These data have high authenticity and representativeness, and can meet the experimental requirements. In the experiment, a construction method of CAD industrial product life cycle management system based on Apriori algorithm is proposed. By optimizing the time waste rate of CPU and the success rate of main task, this method realizes the overall improvement of system performance. The specific implementation process includes data preprocessing, feature extraction, Apriori algorithm application and other steps. If min sup=1 and min conf=10 are preset, the rule set shown in Figure 3 can be obtained.

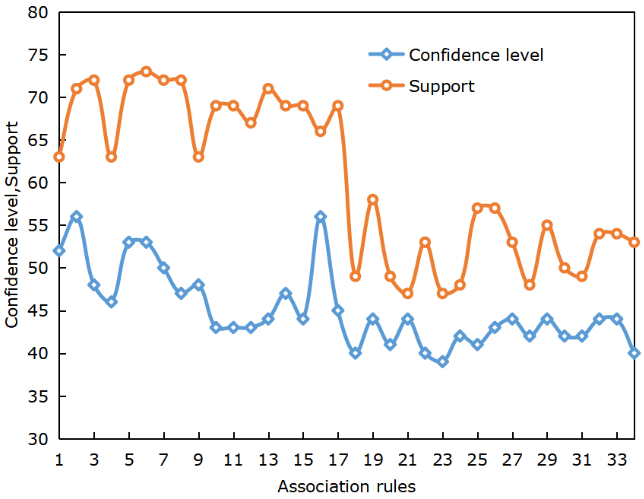

Figure 3: Generated rule set.

Figure 3 shows the variation of strong association rules with different support and confidence thresholds. In association rule mining, support and confidence are two important metrics. Support reflects the universality of rules in all transactions, while confidence measures the reliability of rules. In many application scenarios, we may need to set an appropriate threshold to determine what kind of association rules are meaningful. When the support threshold is fixed at 1, with the increase of confidence threshold, the quantity of strong association rules may gradually decrease. This is because under the high confidence threshold, only those rules with very high confidence can be identified as strong association rules. This can reflect that with the increase of confidence threshold, the strictness of judging strong correlation is also increasing. When the confidence threshold is fixed at 10, the quantity of strong association rules may gradually increase with the increase of the support threshold. This is because under the high support threshold, only those association rules that appear in a large quantity of transactions can be identified as strong association rules. This can reflect that with the increase of support threshold, a wider range of association rules can be accepted. The execution time of the synchronization algorithm is shown in Figure 4.

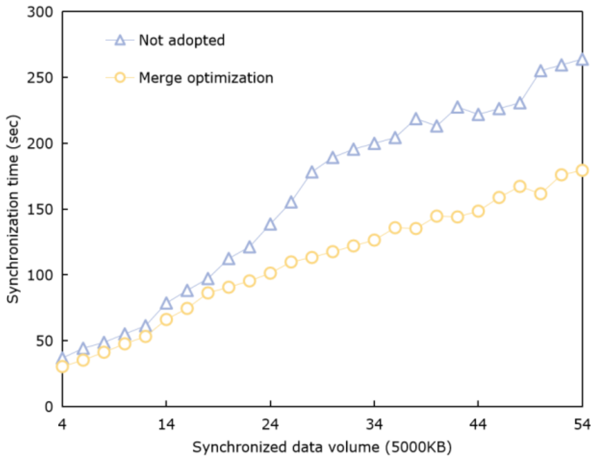

Figure 4: Execution time of synchronization algorithm.

In Figure 4, the execution timeline of the traditional synchronization algorithm is represented as a vertical line from left to right. The execution time of this synchronization algorithm is relatively long. This may be because the traditional synchronization algorithm needs more steps and operations when processing data, such as multiple data exchanges between cache and database, and complex calculations and operations when processing data. In contrast, the execution timeline of the record merging optimization algorithm is represented as a diagonal line from left to right. The execution time of this algorithm is obviously less than that of the traditional synchronization algorithm.

The system synchronization algorithm is executed according to the time stamp, but in the original method, the bad tuples will be updated with the increase of the number of terminal clients after synchronization (Figure 5).

By adding semantic information to the synchronization process, the amount of data to be transmitted can be effectively reduced. This is because semantic information can help the algorithm identify which data are similar or duplicate, so as to avoid transmitting these data during synchronization. Secondly, the synchronization algorithm based on semantic transaction merging optimization can also effectively reduce the execution time of synchronization algorithm. This is because the algorithm reduces the amount of data that needs to be synchronized by merging similar or repeated transactions, thus improving the efficiency of synchronization.

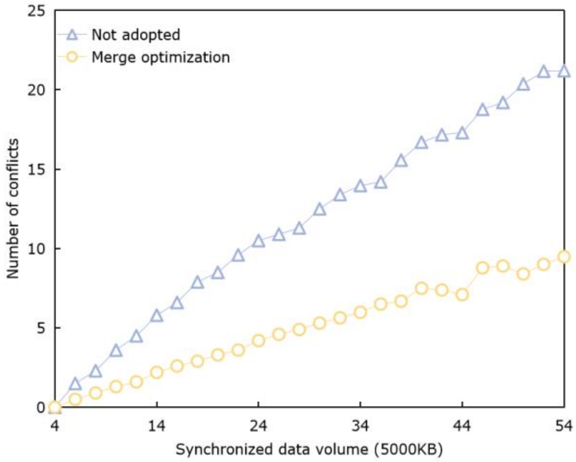

Figure 5: Number of conflicts in transactions.

Figure 6 shows the utilization of computing units under different workloads. It can be seen that with the increase of workload, the utilization rate and average operation time of various algorithms have changed.

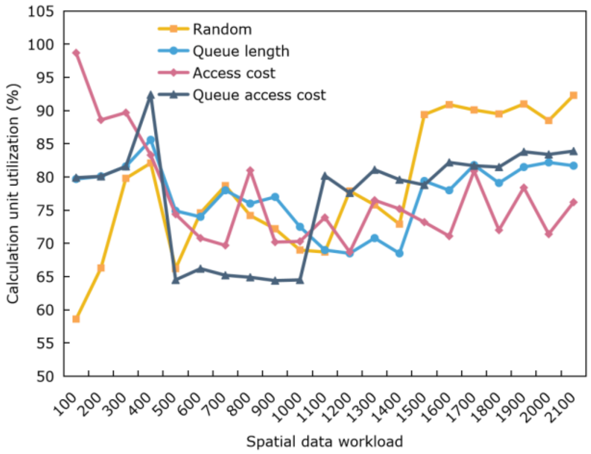

Figure 6: The workload of different algorithms and the utilization rate of spatial data processing units.

With the increase of workload, the average operation time of random algorithm increases gradually and becomes very unstable. This is because the random algorithm does not take into account the balance of queue length and processing time. With the increase of workload, the average operation time of queue length algorithm increases gradually, but it is relatively stable. With the increase of workload, the average operation time of access cost integration algorithm increases gradually, but it is still relatively low. This is because the access cost integration algorithm fully considers the queue length and processing time, which forms the load balance between spatial data processing units, thus improving the performance.

Figure 7 describes the influence of *Apriori* algorithm on the time waste rate of system CPU and the success rate of main task.

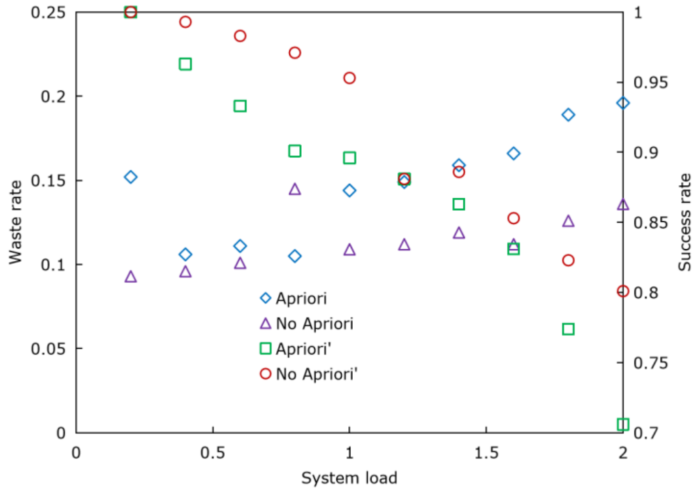

Figure 7: Influence of Apriori on CPU waste rate and task success rate.

In the left graph (CPU time waste rate), Apriori algorithm effectively reduces the waste of CPU time by avoiding preempting low-priority tasks that are about to be completed and take a long time to execute. This can be achieved by delaying the execution of such low-priority tasks until the completion of higher-priority tasks during task scheduling. In the right half of the graph (main task success rate), due to the optimization of Apriori algorithm, although the execution of low-priority tasks is delayed, their execution time will not be shortened. This means that the execution time of these low-priority tasks can be used by other main tasks. On the whole, Apriori algorithm not only improves the system efficiency by reducing CPU time waste, but also enhances the overall performance of the system by improving the success rate of the main task. This algorithm embodies the dual consideration of optimization strategy, which not only pays attention to the execution of a single task, but also considers the improvement of the performance of the whole system.

6 CONCLUSION

In the traditional PLM system, all kinds of data and information involved in the product design stage are often scattered in different systems and departments. These data include product design data, process planning data, manufacturing data and product use data. This article presents a method of constructing PLM system based on DM. It is found that the Apriori algorithm improves the success rate of the main task by optimizing the task scheduling strategy. The results show that with the introduction of the algorithm, the success probability of the main task is obviously increased, and the overall performance of the system is significantly improved. Moreover, the algorithm can realize the effective utilization of system resources in the implementation process, and further improve the efficiency of energy management. The performance and efficiency of this algorithm are better than traditional methods when dealing with large-scale data sets or complex tasks. This breakthrough method has a potential application prospect, which provides new ideas and enlightenment for subsequent related research.

The specific implementation stage of Apriori algorithm still needs further in-depth research and improvement. For example, the performance and efficiency of the algorithm in dealing with large-scale data sets or complex tasks need to be assessed more comprehensively. This study mainly focuses on theoretical analysis and experimental verification, and lacks testing in practical application scenarios. In the future, the algorithm can be applied to specific practical scenarios for further testing and optimization.

7 ACKNOWLEDGEMENT

This work was supported by Tianjin Municipal Education Commission Scientific Research Program, Research and Implementation of Product Design System Model Based on Hall 3D Structure (No. 2022KJ034).

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