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Research Article

Application of Data Mining in the Evaluation of Enterprise Lean Management Effect

Jinpeng Yang [1] and Ying Liu [2]

[1] *School of Harbin Institute of Technology, Harbin 150001, China*
[2] *School of Business, Jinggangshan University, Jian 343009, China*

Correspondence should be addressed to Ying Liu; liuying1979@jgsu.edu.cn

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In order to improve the effect of enterprise lean management, this study proposes a lean data mining algorithm based on the characteristics of lean data in enterprise management. This study connects data mining and lean production to study the data of enterprise management operation, proposes an intelligent data processing model suitable for modern enterprise management, and constructs the model function module in combination with the enterprise operation management process. Moreover, this study constructs an evaluation system for the effect of enterprise lean management based on data mining. The system provides a human-computer interaction interface, and operators can use various functions and services provided by the system through a visual interface. Through experimental research, it can be known that the enterprise lean effect evaluation system based on data mining proposed in this study can play an important role in enterprise lean management.

1. Introduction

With the formation of China's position as the world's manufacturing center, the problem of how to improve the utilization of manufacturing resources and improve production efficiency has become increasingly prominent, and lean production has received increasing attention as a management method to eliminate waste and improve efficiency. In-depth promotion of the practice of lean production objectively requires some support from the related theoretical research of lean production [1]. It can be seen that both objective practice and theoretical circles need to further deepen lean-related research. In the 21st century, the methods and experience of achieving lean have become more abundant and mature. During this period, digital manufacturing has provided more powerful tools for the realization of lean and expanded the scope of application of lean thinking in manufacturing enterprises. In the past, we emphasized quality, efficiency, and cost control in the manufacturing process. However, in fact, the design process also needs to pursue high quality, high efficiency, and low cost. That is, we need to extend the "lean" thinking from manufacturing to design and use the best solution as much as possible in every link, step, and process of design. At the same time, it can accurately control and optimize the design process and state in the design activity, so as to achieve the highest product value and the lowest cost [2]. It is based on this demand that lean thinking is applied to the design stage, and the problems that may arise in the future operation of the enterprise will be eliminated from the design stage. This mode of operation can avoid the fundamental elimination of waste in the enterprise and avoid the "remedy" practice of improving after problems arise in the operation of the enterprise [3].

The continuous and dynamic economic and social competitive environment has intensified competition among enterprises and brought challenges to the survival and development of enterprises. How to deal with the dynamic changes of the current economic and social competitive environment has become one of the hot issues that academia and business circles pay attention to. It is generally believed that innovation is a powerful weapon for companies to survive and develop in a continuous dynamic environment. If companies want to occupy a favorable position in fierce competition, they must continue to innovate. Although the academic circles have different understandings of the innovation system, they all agree that management innovation and technological innovation are the indispensable content of the enterprise innovation system, and they are also the two cores of enterprise innovation. However, enterprise innovation is a systematic project, which requires not only technological innovation but also continuous promotion of management innovation.

Enterprises, especially manufacturing enterprises, as the engine of the country's industrialization and modernization, are the production departments with complex technology and the most advanced technologies. More than 7% of the scientific research funds in developed countries are used for the construction and research of manufacturing technology. It can be seen that technological innovation is of the importance of enterprises (especially manufacturing). However, because technological innovation can be clearly reflected in products, managers in enterprises pay too much attention to technological innovation and neglect management innovation, causing many enterprises to encounter bottlenecks in the middle of their development. The proposal of enterprise innovation tasks, the organization of power, the allocation of resources, the incentive and coordination of the process, etc., are inseparable from the management's strategic vision, innovation guidance, and mechanism support. Therefore, it can be said that management innovation is the locomotive of enterprise innovation. Many Chinese companies can design and trial produce advanced samples, but it is more difficult to ensure the quality of their mass production, and the unit consumption of resources is much higher than the international level, and the waste is large. At the same time, the personnel involved in innovation are also less, and these problems are also the main problems faced by most companies that adopt the strategy of in-line and external expansion to become stronger and bigger, because these companies are not facing the pressure of external expansion, but the pressure of in-line lean management innovation. The lean management idea with "full participation, continuous improvement, elimination of waste, creation of value, and stimulation of positive energy" as the core is derived from lean production and is a production organization based on the Toyota Production System (TPS) as a prototype. Based on this method, lean management is derived, that is, the use of lean thinking to manage various activities of the enterprise. This method provides an idea for enterprises to effectively solve management problems in the process of in-line development and promote enterprise management innovation.

2. Related Work

The literature [4] has conducted an in-depth study on the essence of Toyota's production management and found that if the company does not fully integrate lean thinking into the enterprise, the organization's cost management cannot find lean thinking. Based on the TOC theory and accounting system, an analysis model that combines the basic operating characteristics of lean production methods with the practical application of the enterprise management information system is proposed to achieve the goal of the lowest cost of the enterprise. The literature [5] puts forward the concept of lean accounting, which is based on the comparison of standard cost and value stream cost. The literature [6] proposed that value stream cost management can make enterprise cost decisions more accurate, so it has very important significance for lean enterprises.

Literature [7] designed a lean cost management system with wider applicability based on the Toyota cost accounting system. As a result, lean cost management began to prevail all over the world. Literature [8] proposes how to conduct cost management under the lean accounting system: cost management with value flow as the core does not require annual budgets, and the calculation of performance appraisal indicators is not based on historical data but is oriented to the future status of the enterprise. Literature [9] reviewed the development process of lean management and explained its connotation and proposed that lean cost management is based on the correct understanding of value flow, and the smooth flow of value flow is guaranteed. The vitality of lean cost management comes from continuous improvement and the pursuit of perfection. The key to this is that customers should act as the driving force of the value stream. Literature [10] puts forward the theoretical framework of lean cost management, aiming at low-cost, high-efficiency, and high-quality production, with just-in-time production and the self-consciousness of personnel as the pillars, to eliminate all waste from point to surface and be uninterrupted based on the improvement activities. Literature [11] puts forward the five basic principles of lean cost management: customers determine the product value structure, eliminate waste in the industrial value chain, turn batches and queues into a continuous flow, drive the value chain by customer demand, and pursue perfection. Literature [12] puts forward a lean accounting viewpoint that is different from the previous accounting viewpoints. Its goal is customer value, the core of management is value flow, and the ultimate goal is to eliminate waste. Taking value stream costing analysis and assessment as the entry point, the implementation process of lean accounting is discussed in depth and detail, which provides a highly operational guiding framework for lean enterprise cost management. From the perspective of lean management accounting, literature [13] explains the obstacles, such as corporate culture obstacles, financial role transition obstacles, educational background obstacles, and employee personal obstacles, encountered when applying lean accounting theory to implement cost management. Literature [14] summarizes the basic content of lean accounting, including value stream costing, analysis, and management and proposes the principles of lean accounting: group work, self-responsibility, and regular improvement. Literature [15] pointed out the inapplicability of the traditional accounting indicator system to lean organizations, thereby constructing a new performance measurement indicator system for lean organizations. The indicator system includes the value stream level and the production unit level and fully combines the characteristics of lean production. Literature [16] demonstrates the four-level structure model of lean cost management, lean basis, lean functions, lean methods, and lean objectives. Literature [17] believes that lean cost management can help Chinese companies effectively cope with the economic crisis and pointed out that lean cost management with the elimination of waste as the core embodies the spirit of innovation, shows corporate culture, and contains social responsibility. Literature [18] proposes that in the process of implementing lean cost management, enterprises must adhere to the four principles of combination: refinement, simplification and quantification, revenue increment and waste elimination, stock revitalization and incremental optimization, and local optimization and overall coordination. Literature [19] starts with the shaping of lean cost values and explains the importance and feasibility of lean construction. Literature [20] constructed a cost management system that focuses on value stream cost management, including cost decision-making, cost accounting, cost analysis, and cost assessment. Literature [21] proposes that lean cost management can effectively reduce waste in the production and operation of enterprises, has conducted research on improving the operation process of lean enterprises and the efficient use of lean cost management, and has provided operable applications for enterprises in management practice methods.

3. Lean Management Data Mining Algorithm

The time series is $X_1, X_2, \ldots, X_N$ with N-ordered observations that can be regarded as a part of the random process $\{X_t \mid t = 0, \pm 1, \pm 2\}$, and the observation value of the time series is $x_1, x_2, \ldots, x_N$.

Stationarity is the following: if the time series is $X_1, X_2, \ldots, X_N$, it can be called weakly stationary or second-order stationary. The following conditions need to be met: the mean value of X_t (mathematical expectation) does not change with time. That is, for any t, $E(X_t) = \mu$ (where μ is a constant). Moreover, for any lag period τ, the correlation coefficient between X_t and $X_{(t+\tau)}$ is $\mathrm{Cov}(X_t, X_{(t+\tau)}) = \gamma_t$, that is, the correlation coefficient only depends on τ and has nothing to do with time t. Obviously, the variance of a stationary time series is also a constant: $\mathrm{Var}(X_t) = \gamma_0$. In general practical applications, it is enough to focus on weak stationarity.

The backshift operator is as follows: B is defined as $By_t = t_{(t-1)}$. Obviously, $\nabla = 1 - B$. Among them, ∇ is the difference operator, and there is $\{X_1, X_2, \ldots, X_N\}$ for the sequence $\nabla_s X_t = X_t - X_{(t-s)}$. The backshift operator has the following properties:

$$\begin{aligned} B^s y_t &= y_{(l-s)}, \\ \frac{1}{(1-\alpha B)} y_t &= \left\{1 + \alpha B + \alpha^2 B^2 + \cdots\right\} y_t \\ &= y_t + \alpha y_{(t-1)} + \alpha^2 y_{(t-2)} + \cdots \text{ or } |\alpha < 1|. \end{aligned} \tag{1}$$

White noise is as follows: if all observations of sequence $\{w_t\}$ are independent and identically distributed, and other mean μ and variance σ^2 are finite constants, it is called white noise or pure random process. The definition of white noise is represented by the symbol:

$$w_t = ii\ d\left(\mu, \sigma^2\right). \tag{2}$$

If the distribution of white noise is a normal distribution with a mean value of 0, $\{w_t\}$ also becomes Gaussian white noise.

The MA model is as follows: it is assumed that $\{w_t\}$ is a white noise sequence with a mean value of 0 and a variance of σ^2. If the sequence $\{X_t\}$ satisfies,

$$X_t = \mu + w_t + \theta_1 w_{(t-1)} + \cdots + w_{(t-q)}. \tag{3}$$

Then, it is called the q-order MA process, that is, the q-order moving average process (moving average process), denoted as MA(q). If $\theta(B) = 1 + \theta_1 B_1 + \cdots + \theta_2 B^2 + \cdots + \theta_q B^q$, the model is

$$X_t = \mu + \theta(B) w_t. \tag{4}$$

AR model is as follows: the hypothesis is a white noise sequence with a $\{w_t\}$ mean value of 0 and a variance of σ^2. If the sequence $\{X_t\}$ satisfies,

$$X_t = \theta_1 X_{(t-1)} + \cdots + \theta_p X_{(t-p)} + w_t. \tag{5}$$

Then, it is called the p-order AR process, that is, the p-order autoregressive process (moving average process), denoted as AR(p). If the X_t mean value is not 0, the above equation is equivalent to

$$X_t = \alpha + \phi_1 X_{(t-1)} + \cdots + \phi_p X_{(t-p)} + w_t. \tag{6}$$

In the formula, $\alpha = (1 - \phi_1 + \cdots + \phi_p)\mu$. If $\phi(B) = 1 - \phi_1 B^1 - \phi_2 B^2 + \cdots - \phi_p B^p$, the model is

$$\phi(B) X_t = \alpha + w_t. \tag{7}$$

If we consider B as a complex variable,

$$\phi(B) = 0. \tag{8}$$

It is called the characteristic equation of the AR model.

The ARMA model is as follows: if the expectation of X is $\mu = 0$, then the autoregressive average process ARMA(p, q) is defined as

$$X_t = \phi_1 X_{(t-1)} + \cdots + \phi_p X_{(t-p)} + w_t + \theta_1 w_{(t-1)} + \cdots + \theta_p w_{(t-p)}, \tag{9}$$

or $\phi(B) X_t = \theta(B) w_t$ and $\theta(B) = 1 + \theta_1 B + \cdots - \theta_p B^q$. If it is expected that μ is not equal to 0, the above definition can be written as

$$\begin{aligned} X_t = \phi_0 &+ \phi_1 X_{(t-1)} + \cdots + \phi_p X_{(t-p)} + w_t + \theta_1 w_{(t-1)} \\ &+ \cdots + \theta_p w_{(t-p)} \end{aligned} \tag{10}$$

and $\phi_0 = (1 - \phi_1 - \ldots - \phi_p)\mu$.

We assume that $\{w_t\}$ is a white noise sequence with variance σ^2, and we consider an ARMA sequence with a mean of 0.

$$\phi(B)X_t = \theta(B)w_t. \tag{11}$$

The sequence can be written as

$$X_t = \frac{\theta(B)}{\phi(B)}w_t = \psi(B)w_t = w_t + \psi_1 w_{(t-1)} + \psi_2 w_{(t-2)} + \cdots. \tag{12}$$

Our goal is to predict the future value q of m steps based on the past $(X_n, X_{(n-1)}, \ldots, X_1)$ up to n hours. The predicted value is $X_{(n+m)}$. In ntm, there are

$$X_{(n+m)} = \sum_{j=0}^{\infty} \psi_j w_{(n+m-j)} = \sum_{j=0}^{m-1} \psi_j w_{(n+m-j)} + \sum_{j=m}^{\infty} \psi_j w_{(n+m-j)}. \tag{13}$$

Among them, $\sum_{j=0}^{m-1}\psi_j w_{(n+m-j)}$ represents the future w, and $\sum_{j=m}^{\infty}\psi_j w_{(n+m-j)}$ represents the past w. We want to express $\widehat{X}_n(m)$ as a linear combination of these $w_1, w_{(n-1)}, \ldots$.

$$\widehat{X}_n(m) = \psi_m^* w_n + \psi_{(m+1)}^* w_{(n-1)} + \psi_{(m+2)}^* w_{(n-2)} + \cdots. \tag{14}$$

Therefore, it is necessary to find the coefficient ψ_j^* that minimizes the mean square error, and the mean square error is

$$E\left(X_{n+m} - \widehat{X}_n(m)\right)^2. \tag{15}$$

$$E\left(X_{n+m} - \widehat{X}_n(m)\right)^2 = \sigma^2 \sum_{j=0}^{m-1} \psi_j^2 + \sigma^2 \sum_{j=0}^{\infty}\left(\psi_{(m+j)} - \psi_{(m+j)}^*\right). \tag{16}$$

Therefore, we require

$$\frac{\partial E\left(X_{n+m} - \widehat{X}_n(m)\right)^2}{\partial \psi^*} = -2\sigma^2 \sum_{j=0}^{\infty}\left(\psi_{(m+j)} - \psi_{(m+j)}^*\right) = 0. \tag{17}$$

This results in $\psi_{(m+j)} = \psi_{(m+j)}^*$, that is,

$$\widehat{X}_n(m) = \psi_m w_n + \psi_{(m+1)} w_{(n-1)} + \psi_{(m+2)} w_{(n-2)} + \cdots. \tag{18}$$

From another perspective, $X_{(n+m)}$ can be expressed as

$$X_{(n+m)} = \sum_{j=0}^{\infty} \psi_j w_{(n+m-j)} = \sum_{j=0}^{m-1} \psi_j w_{(n+m-j)} + \sum_{j=0}^{\infty} \psi_j w_{(n-j)}. \tag{19}$$

We know that when past information $I_n = \{X_n, X_{n-1}, \ldots\}$ is given, the best prediction for $X_{(n+m)}$ is

$$E\left(X_{(n+m)} \mid I_n\right) = E\left(\sum_{j=0}^{m-1} \psi_j w_{(n+m-j)} | I_n\right) + E\left(\sum_{j=0}^{\infty} \psi_j w_{(n-j)} | I_n\right) = 0 + \sum_{j=0}^{\infty} \psi_j w_{(n-j)}. \tag{20}$$

Therefore,

$$\widehat{X}_n(m) = E\left(X_{(n+m)} \mid I_n\right)^2 = \sum_{j=0}^{\infty} \psi_j w_{(n-j)}. \tag{21}$$

We get the prediction error

$$P_n(m) = X_{(n+m)} - \widehat{X}_n(m) = \sum_{j=0}^{m-1} \psi_j w_{(n+m-j)} = w_{(n+m)} + \psi_1 w_{(n-k+m)} + \cdots + \psi_{(m-1)} w_{(n+1)}. \tag{22}$$

This is an MA $(m-1)$ process with a mean of 0 and a variance of $\sigma^2 \sum_{j=0}^{m-1} \psi_j^2$. $P_n(m)$ is relevant for $m > 1$, and it is

$$P_{n-k}(m) = \sum_{j=0}^{m-1} \psi_j w_{n-k+m-j} = w_{n-k+m} + \psi_1 w_{n-k+m-1} + \cdots + \psi_{m-1} w_{n-k+1}. \tag{23}$$

Therefore, the covariance of the prediction error is

$$\operatorname{cov}\left(P_n(m), P_{(n-k)}(m)\right) = \sigma^2 \sum_{l=n+1}^{n+m-k} \psi_{(l-n)}\psi_{(l-n-k)}, \quad k<1. \tag{24}$$

The basic idea of the ARMA forecasting model is to assume that the corresponding sequence $\{y_t\}$ and the input variable sequence (independent variable sequence) $\{x_t\}(u = 1, 2, \ldots, k)$ are both stationary. It first builds a regression model of the response sequence and the input variable sequence. Since both $\{y_t\}$ and $\{x_t\}(u = 1, 2, \ldots, k)$ are stationary, and the linear combination of stationary series is also stationary, the residual series $\{\varepsilon_t\}$ is a stationary series $\{\varepsilon_t\}$. Subsequently, it uses the ARMA model to continue to extract the residual sequence $\{\varepsilon_t\}$. Finally, the model can be obtained as equation (22). The prediction process is shown in Figure 1.

The basic ARMA model uses the unary time series analysis method. In reality, many time series are affected by other time series in addition to their own changing laws. The introduction of relevant time series can increase the fit of the ARMA model. If the input sequence is a leading indicator, the lag of the ARMA forecast will be improved, and the forecast value of the model will be more accurate.

The ARMAX model improves the prediction of the input sequence by using the historical information of the output sequence and its related input sequence, and it has the following structure:

$$\left\{ y_t = \mu + \sum_{l=1}^{k} \frac{\Theta_l(B)}{\Phi_l(B)} B^{l_1} x^{lt} + \varepsilon_t \varepsilon_t = \frac{\Theta_l(B)}{\Phi_l(B)} w_t. \right. \tag{25}$$

In the formula, $\Phi_l(B)$ represents the autoregressive coefficient polynomial of the ith input variable, $\Theta_l(B)$ represents the average coefficient polynomial of the ith input variable, $1i$ represents the delay order of the ith input variable, and $\{\varepsilon_t\}$ represents the regression residual sequence. $\Theta_l(B)$ represents the autoregressive coefficient polynomial of the residual sequence, $O(B)$ represents the moving average coefficient polynomial of the residual sequence, and $\{w_t\}$ represents the zero-mean white noise sequence.

The basic idea of the ARMAX forecasting model is to assume that the corresponding sequence $\{y_t\}$ and the input variable sequence (independent variable sequence) $\{x_t\}(u = 1, 2, \ldots, k)$ are both stationary. First, it constructs a regression model of the response sequence and the input variable sequence. Since both $\{y_t\}$ and $\{x_t\}(u = 1, 2, \ldots, k)$ are stationary, and the linear combination of stationary sequences is also stationary, the residual sequence $\{e,\}$ is the stationary sequence $\{\varepsilon_t\}$. Subsequently, it uses the ARMA model to continue to extract the residual sequence $\{\varepsilon_t\}$. Finally, the model can be obtained as equation (22), and the prediction process is shown in Figure 2.

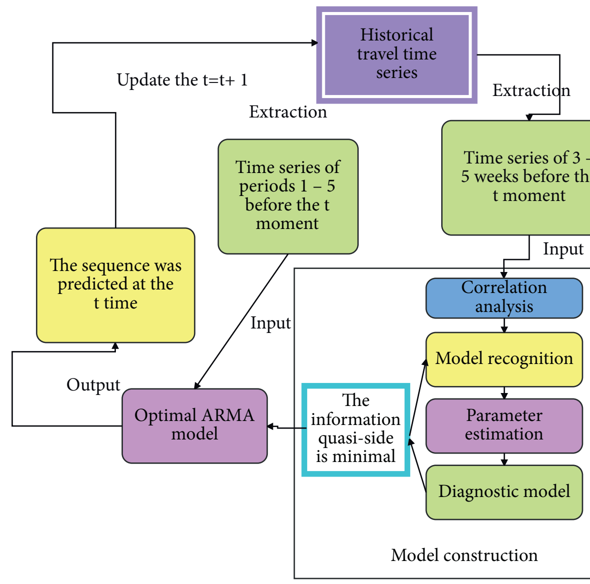

Figure 1: ARMA predictive model process.

4. Evaluation of the Effect of Enterprise Lean Management Based on Data Mining

For a manufacturing system, the demand for raw materials or parts is closely related to the demand for finished products and cannot be simply regarded as an independent demand. Moreover, the manufacturing method has experienced the evolution from handmade to mass production and then to lean production and as shown in Figure 3.

Lean production is a comprehensive technological system that encompasses a variety of manufacturing technologies and management technologies. The composition of lean production mainly includes the following: kanban-based production control, total quality management, participation of all employees in decision-making, and supplier collaboration. Lean production strictly organizes production according to orders through the kanban control method, transmits material demand information between processes through kanban, and uses kanban to delegate production control to the subsequent processes of each process. The technical system structure of lean production is shown in Figure 4.

The planning level of the batch production model in the small-batch environment of the variety is shown in the following Figure 5.

Figure 6 shows the hardware composition model of the lean production management system. The monitoring system adopts the B/S model in architecture. System software and related databases only need to be installed on the server side. Moreover, the computers connected by various departments do not need to be installed as clients and only need to use a browser to use the production monitoring system. Using this hardware composition model has the following advantages: ① investment is low. In addition to purchasing computers, hardware equipment of the original network system is basically used. ② In the process of system

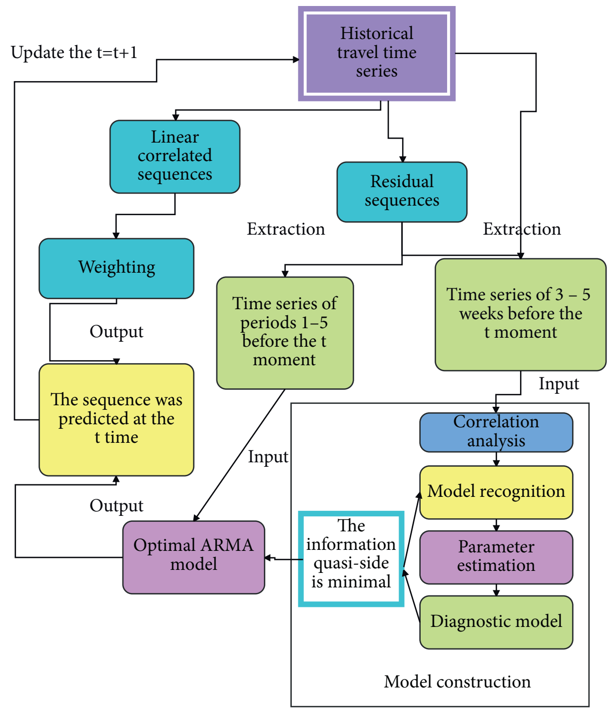

Figure 2: ARMAX prediction model process.

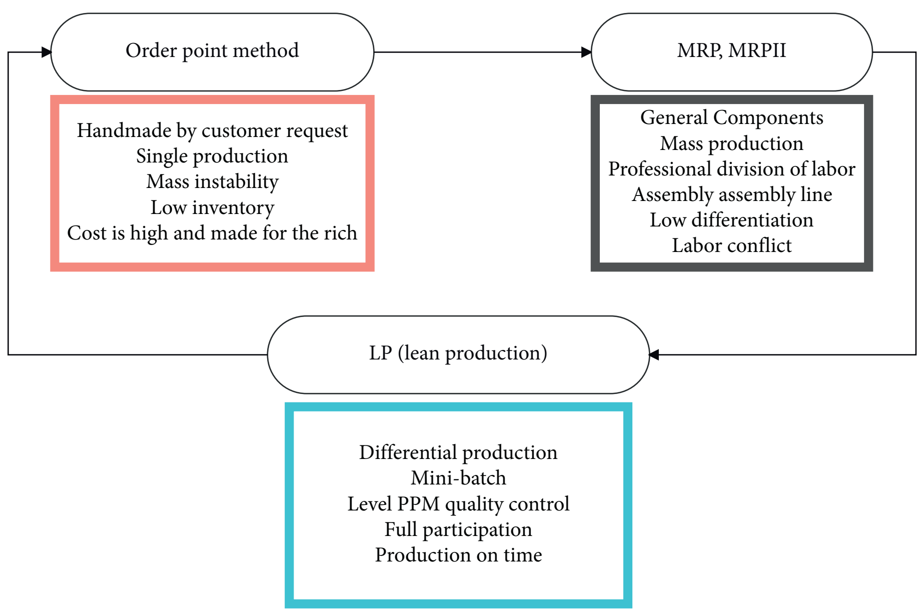

Figure 3: Evolution of manufacturing methods.

transformation, production can normally proceed without being affected at all. ③ Data are uniformly processed on the server side of the production management system. The front-end program browser is only responsible for displaying the feedback information of the server program, so the computer configuration requirements for each department's access are not high. ④ When the lean production management system needs to be upgraded, it only needs to update the server-side program installed on the production management server and does not need to reinstall the front-end application program, which facilitates the system upgrade.

With the development of internet technology, computing technology is changing from an application system based on the C/S (client/server) model to an application system based on the B/S (browser/server) model. In the B/S model, the core point is to replace the original client program with a general-purpose browser. All configuration work is concentrated on the server side, the security of the system is improved, and it also brings convenience to the

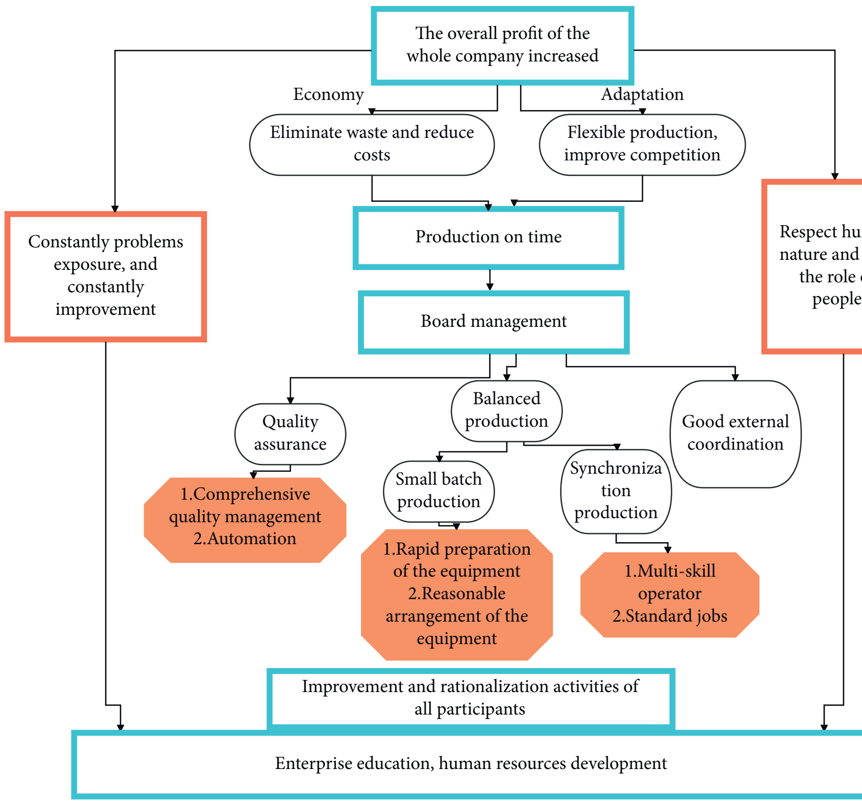

Figure 4: Lean production manufacturing system structure.

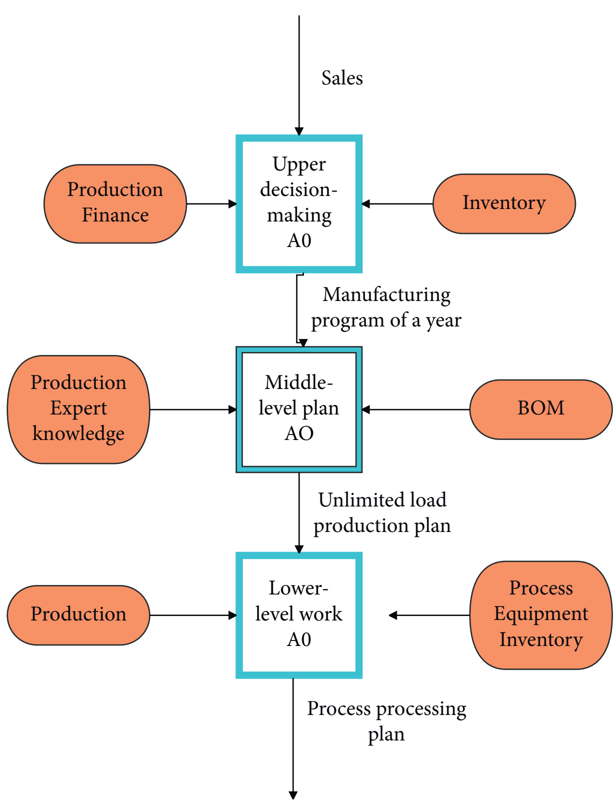

Figure 5: Production planning hierarchy.

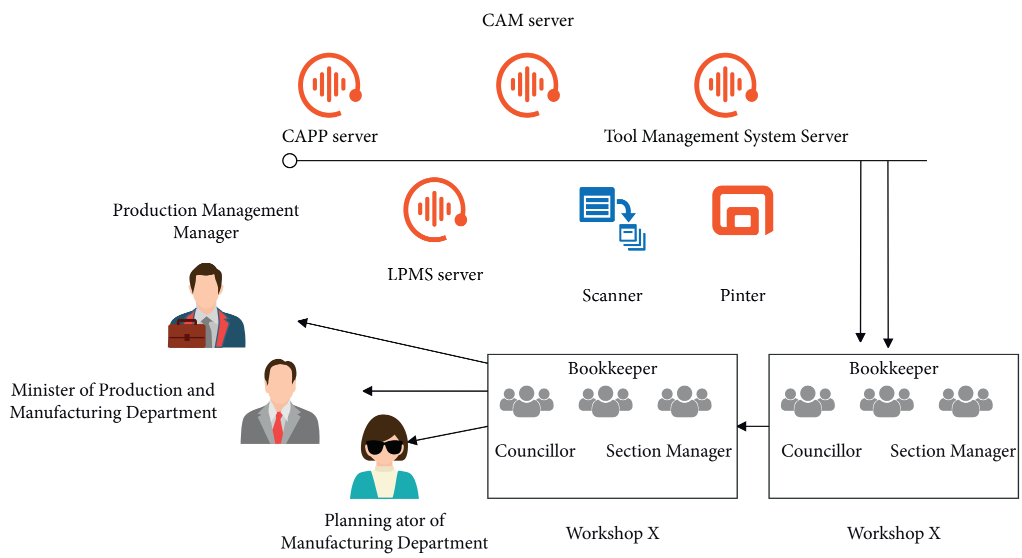

Figure 6: The hardware composition model of the lean production management system.

deployment, upgradation, and maintenance of the program. This study uses B/S application architecture based on J2EE technology to build a lean production management system. In the field of software engineering, in order to reduce the degree of module coupling and improve the reusability of modules, layering has always been a widely adopted method. Layering can also enable developers to focus on a certain layer for development and make the division of software development finer and improve production efficiency. An enterprise level, the J2EE application is usually divided into the following three layers: UI layer, business logic layer, and data persistence layer. A brief introduction to these layers is given below. (1) The UI layer is responsible for interacting with the user, including accepting the user's request and returning the processing result to the user. (2) The business logic layer is mainly responsible for specific business processing. (3) The data persistence layer is mainly responsible for dealing with the underlying database.

The web application in this study is divided into 3 layers in terms of responsibilities, and these three layers are presentation, business, and persistence. Figure 7 is a schematic diagram of the system architecture. Each layer should have a clear responsibility for processing procedures and should not be functionally mixed with other layers, and each layer should be separated from other layers, but a communication interface should be placed between them.

The traditional lean production theory is only applied to the partial implementation process and organizational scope, and its effect can only be reflected in the field and operation level. Therefore, the lean production management system based on VSM will implement lean improvement from project $\longrightarrow$ plan $\longrightarrow$ task $\longrightarrow$ improvement $\longrightarrow$ abnormal. This method is an optimization of the traditional lean production theory, and it is a holistic lean improvement process, rather than applied to the local implementation process and organizational scope. Moreover, its effect will also be reflected in the entire process of lean improvement,

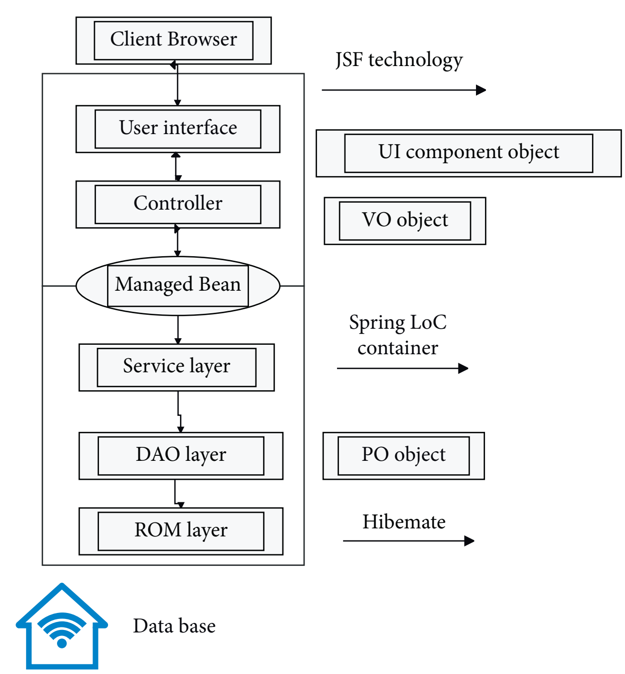

Figure 7: B/S three-tier system structure.

rather than just reflected in the field and operation level. The improvement process of the VSM-based lean production management system is shown in Figure 8.

Project management rules are the supporting framework of the project management model. Project management rules are composed of five modules: project formulation, project review, project monitoring, project statistics, and project summary. The project formulation module is composed of survey information and project details. The survey information includes three aspects of field data, resource allocation, and market conditions. The project details include parameters such as project ID, project name, project constraints, project type, and project content. Constraints

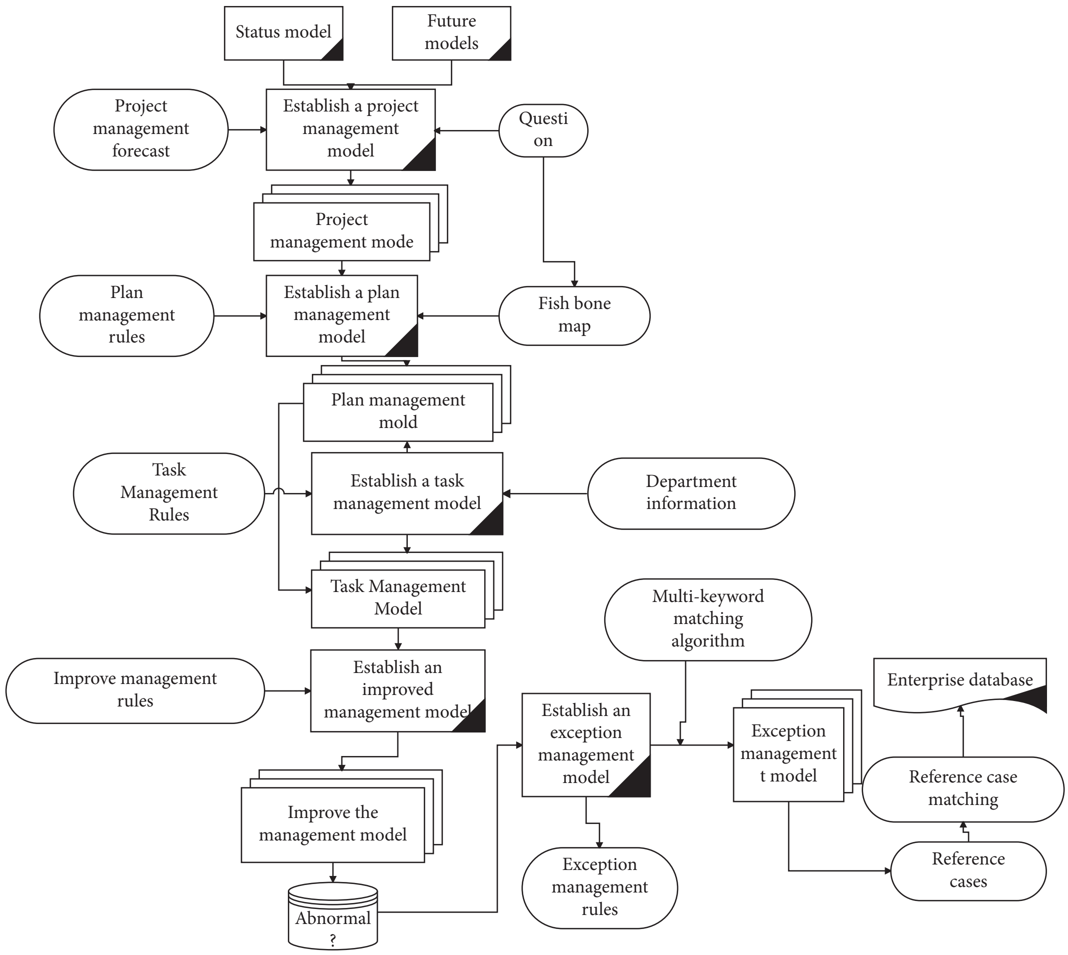

Figure 8: The improvement process of the lean production management system based on VSM.

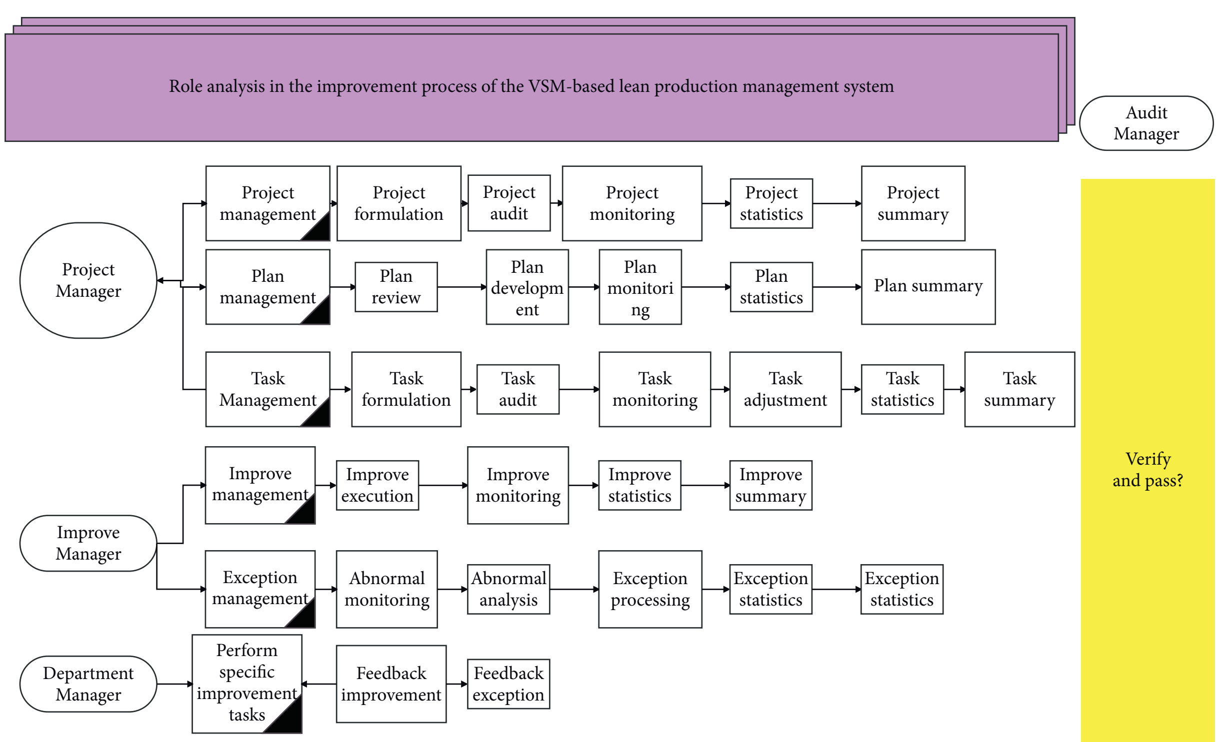

Figure 9: Role analysis in the improvement process of the lean production management system based on VSM.

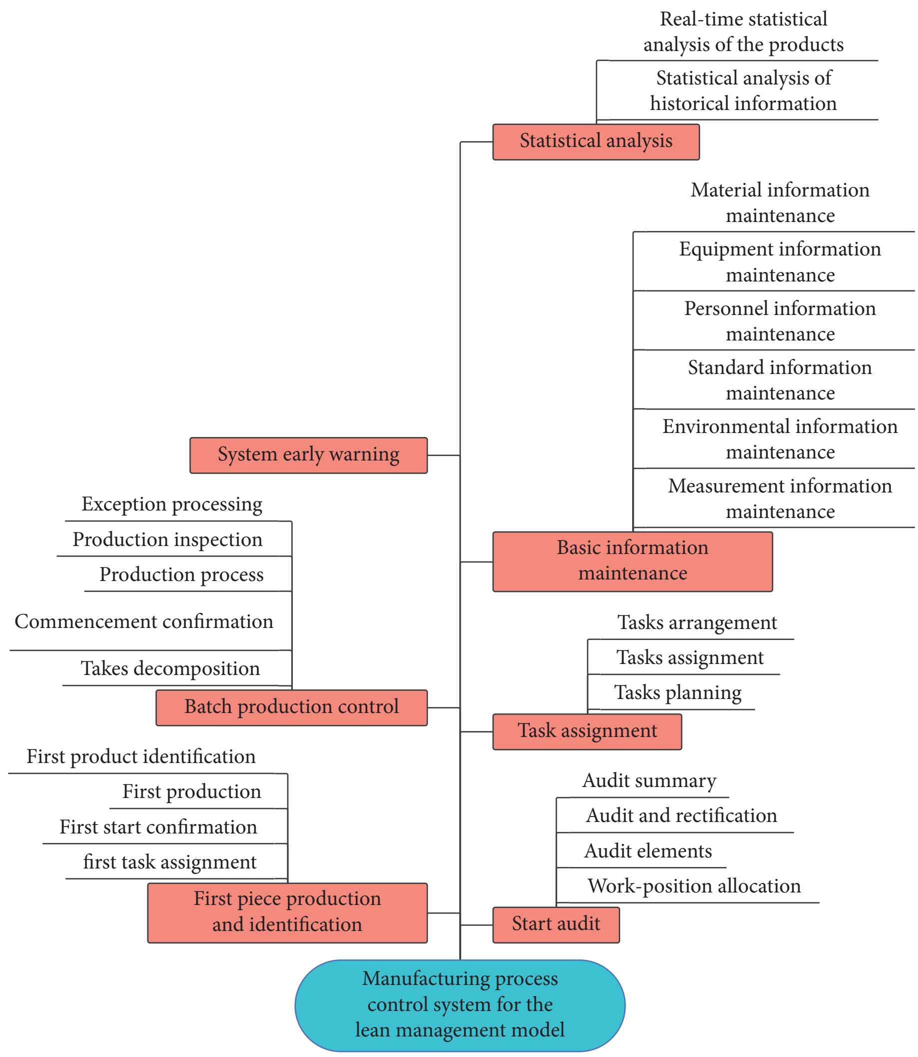

Figure 10: System hierarchy function diagram.

refer to the constraints on the implementation of projects such as expected time limit and budget funds. The second is the project review module. The project review module is mainly for project details, including two points: review content and review results. The review content refers to the project information reviewed, and the review result refers to the evaluation of the project content. The project monitoring module is responsible for real-time monitoring of project implementation, including parameters such as project name, project content, project progress, and project completion. The project statistics module is responsible for information statistics during project execution, including project name, project content, number of employees, time consumption, material consumption, capital consumption, and completion status. In addition, the project management rules also include a project summary module, which is responsible for the reflection and summary of the project implementation process.

Four roles are set up in the improvement process of the VSM-based lean production management system. After the setting of roles and the analysis of their functions, customers no longer only refer to the final customers but also include other participants in the production of the enterprise. Moreover, it allows everyone to participate in the lean improvement process and solves the defect that traditional lean production theory ignores in enterprise production participants. The following will introduce the functional analysis and definition of the four roles in this method. The role analysis in the improvement process of the VSM-based lean production management system is shown in Figure 9.

It can be seen from the previous analysis that a top-down analysis method is adopted. The system can be abstracted into subsystems such as start-up review, task allocation, first-article production and appraisal, basic data maintenance, mass production process control, system early warning, and statistical analysis. Moreover, each subsystem can be divided into several modules according to its function. The hierarchical functional structure of the system is shown in Figure 10.

On the basis of the above models, combined with data mining algorithms, an evaluation model for the effect of enterprise lean management is constructed. In order to

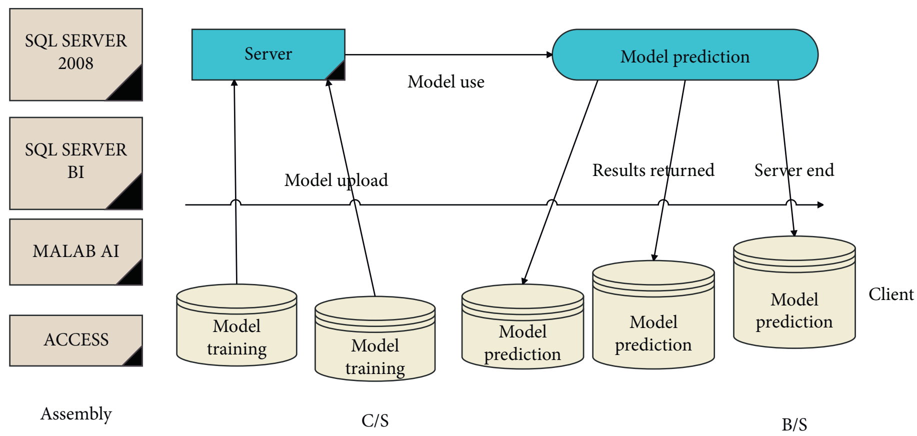

Figure 11: Quality prediction system based on data mining.

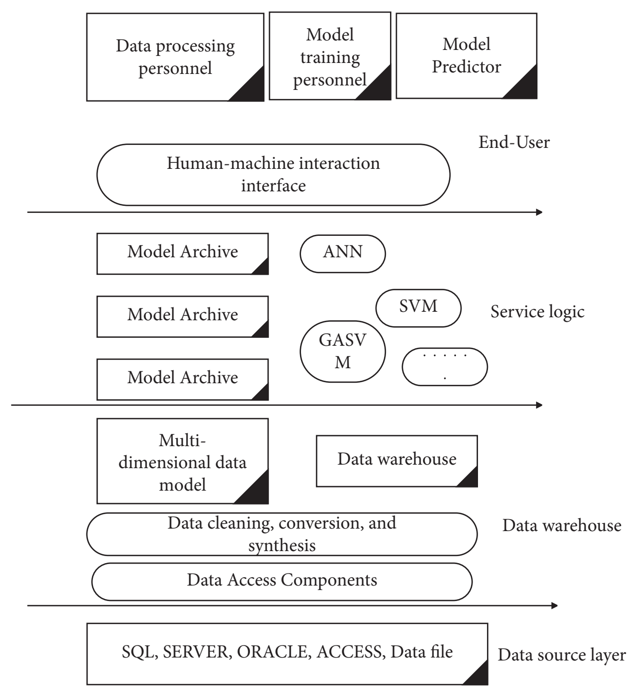

Figure 12: The evaluation model of enterprise lean management effect based on data mining.

facilitate deployment and rational use of system resources, the system adopts C/S and B/S hybrid architecture model for development. The model training client uploads the model file to the server, and the model prediction client directly returns the result calculated on the server. Due to the need to call some computing components, the server and the model training client take up a lot of system resources (as shown in Figure 11). The system ultimately faces three types of users: data processing personnel, model training personnel, and model prediction personnel. The data processing personnel perform data loading and data cleaning operations, and the model training personnel are responsible for the training of the model. They upload the models that meet the conditions to the server for use. Model forecasters can directly use the model files on the server through a browser. Therefore, the system provides a human-computer interaction interface, and operators use various functions and services provided by the system through a visual interface, as shown in Figure 12.

After constructing an enterprise lean effect evaluation system based on data mining, we evaluate the lean data mining, problem discovery, data processing, and management evaluation of the system in this study. The results are shown in Table 1 and Figure 13.

From the above research, the enterprise lean effect evaluation system based on data mining proposed in this study can play an important role in enterprise lean management.

Table 1: Performance verification of enterprise lean effect evaluation system based on data mining.

Number	Data mining	Problem discovery	Data processing	Management evaluation
1	91.72	86.52	87.32	81.72
2	89.62	92.94	95.63	80.96
3	86.47	76.87	89.13	89.16
4	85.41	85.30	75.77	88.42
5	82.85	88.68	77.70	82.62
6	93.30	84.73	85.45	93.49
7	93.86	84.09	89.38	93.31
8	90.76	92.79	83.83	96.97
9	82.87	86.12	91.24	88.86
10	87.92	87.77	94.58	91.48

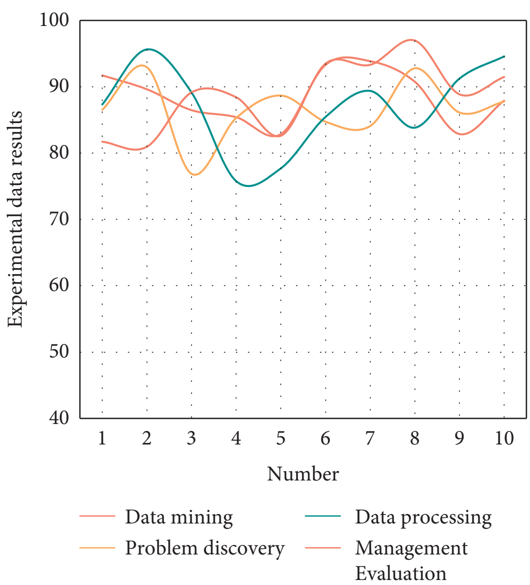

Figure 13: Statistical diagram of system performance test data results.

5. Conclusions

The secret of lean production is that it is not only a production method but also reflects an advanced management idea. It uses product production processes as clues to organize closely related supply chains. On the one hand, it reduces transaction costs in enterprise collaboration, and on the other hand, it ensures stable demand and timely supply and takes the entire mass production system as the optimization goal. As the application of database management systems becomes more and more widespread, the scale of the database is constantly expanding, and people have accumulated massive amounts of business data, such as customer data, transaction history data, sale records, and so on. These databases contain a lot of valuable business information. At present, although the applied database system can efficiently realize data entry, query, statistics, and other functions, it cannot find the relationships and rules existing in the data and cannot predict the future development trend based on the existing data. Therefore, this study links data mining and lean production to build a data mining-based enterprise lean management effect evaluation system, which improves the efficiency of enterprise lean management.

Data Availability

The labeled dataset used to support the findings of this study is available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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