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Intelligent manufacturing management system based on data mining in artificial intelligence energy-saving resources

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Abstract
At present, the old production management mode has become a stumbling block to the development of enterprises, and the high-end manufacturing technology is still not mature enough. This research mainly discusses the intelligent manufacturing management system based on data mining in artificial intelligence energy-saving resources. The enterprise business management system cannot accurately and timely grasp the actual situation of the production site, and the accuracy and feasibility of the upper-level planning cannot be guaranteed. At the same time, on-site personnel and equipment cannot get practical production plans and production instructions in time, resulting in product backlogs and excessive inventory. On the other hand, equipment is idle and resources are wasted, and the workshop scheduling system loses the corresponding scheduling role. The development of this system is mainly composed of front-end technology, back-end technology and front-end and back-end interaction technology. The interface design of the front end is mainly completed by the windows form application in c#. The interaction between the front and back ends is mainly realized by programming in each control of the form application. Back-end technology is the core content of the system, mainly including two key technologies: mixed programming of C #. Net and MATLAB and C # connecting SQL Server database. The system mainly includes five sub-functional modules: order management, material management, mixed model assembly line balance, assembly line logistics scheduling and system management. Order management and material management are the basis of the system, which provides parameter input for the balance of assembly line and logistics scheduling. The balance of mixed model assembly line is the core function of the system. The balance of mixed model assembly line is carried out by calling the intelligent algorithm written in MATLAB, and the optimal assembly scheme of workstation is displayed to the front end of the system, which reflects the intelligent characteristics of production control system for intelligent manufacturing. The logistics scheduling of assembly line takes the balance result of mixed model assembly line as the premise, takes the balance result as the task sequence input of logistics scheduling, and optimizes the operation efficiency of logistics system (driving path and running time of AGV). The operation results show that the comprehensive energy consumption of 10,000 yuan industrial output value is 401.19 kg standard coal/10,000 yuan, a year-on-year decrease of 6.96%. This study is helpful to the fine management of manufacturing industry.

Keywords Artificial Intelligence · Data Mining · Intelligent Manufacturing · Production Control

1 Introduction

As the manufacturing industry faces the development of industrialization, informationization, and intelligence, the traditional production mode can no longer meet the development needs of the times, and intelligent manufacturing has become the current development direction of the manufacturing industry. As an important part of intelligent manufacturing, real-time monitoring system provides a feasible scheme for solving the problems of information islands and information faults. However, the system has problems in versatility, real-time, traceability, etc. Therefore, the research and development of intelligent manufacturing real-time monitoring system has important theoretical significance and practical application value. With the increase in labor costs, there are currently no workers in factories. How to speed up the process of information construction, through computer digitization,

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lean production, quality tracking, inventory optimization, and intelligent production, has become the consensus of the industry. The development of basic industries, basic data of factories, and the level of development and integration of basic spare parts have become the key to the upgrading of our country's manufacturing industry. The high-end software technology of our country's manufacturing industry still relies more on foreign countries. Therefore, the country advocates independent research and development of intelligent manufacturing software suitable for China's manufacturing characteristics, transforming the production mode of our country's manufacturing industry, and realizing the simultaneous progress of industrialization and informatization. Aiming at the problem of industrial process data transmission in the Internet environment, a communication protocol and data packet scheduling rules are designed, the encapsulation format and meaning of different types of data packets are specified, and different priorities are set for data packets, which guarantees sudden information is notified to the client in time, and on the other hand, the transmission volume of data information is simplified. At the same time, the usage rules and application steps of the communication protocol are explained in detail.

With the progress and innovation of society and science and technology, the manufacturing industry is gradually facing networked and agile development. The production and processing mode of traditional manufacturing is no longer suitable for the rapid development of the information age, and the manufacturing industry is facing increasing pressure. In order to take the lead in the new round of industrial revolution, countries around the world have put forward development strategies suitable for their own development needs. Scholars and enterprises at home and abroad have made great progress in theoretical application research and software product design and promotion. With the continuous progress of China's reform and opening up, the wave of factory informatization is approaching. In the fierce competition, if the factory wants to continue to develop, it needs to implement information deployment throughout the factory. Therefore, the application of information technology and automation technology to the management of Chinese manufacturing factories can truly solve the problems that plague entrepreneurs. The procurement of materials is diversified, and the variety and specifications of products put forward higher requirements for enterprises. Therefore, enterprise intelligent manufacturing has become the inevitable way of enterprise informatization, and it has also become the key to the survival and development of manufacturing enterprises. With the help of the MES system, manufacturing enterprises can realize the scheduling and scheduling of the production plan in the business planning layer, the management and monitoring of equipment, the arrangement and recording of personnel, the monitoring and improvement of the production environment, and the identification and tracking of production materials make the entire production and management process more information and intelligent. Affected by the globalization of the market, in order to gain an advantage in the increasingly fierce market competition, various companies adopt their own production management models and advanced information technology based on different business needs. Process management, warehouse management, equipment management and maintenance, and process management have emerged. Independent systems such as management and production management.

In the face of the demanding requirements of customers' delivery dates, the continuous adjustment of orders, and the modification of more products, the formulation and execution of the upper-level planning management system (ERP, etc.) plan is increasingly affected by the market and actual operations, and adaptability the problem is getting more and more prominent. Manufacturing enterprises in the early stage of informationization have already used basic data management tools, such as Excel and other software management, but these software cannot achieve the ultimate need. Mittal S aims to collect and construct various characteristics, technologies and enabling factors related to intelligent manufacturing in the current knowledge system. Ultimately, it is expected that the selection of these characteristics, technologies, and enabling factors will help to compare and differentiate other initiatives. His result is a comprehensive list of features, technologies, and enabling factors related to smart manufacturing. He also considered the principle of "semantic similarity" to build the foundation for future intelligent manufacturing ontology, as many listed items showed different overlaps; therefore, certain features and technologies were merged and/or clustered. He evaluates derivative structures by matching the characteristics and technology clusters of intelligent manufacturing with the design principles of Industry 4.0 and cyber-physical systems (Mittal et al. 2019). Wang J believes that modern manufacturing systems are increasingly equipped with sensors and communication capabilities, and data-driven intelligence is becoming more and more popular in analyzing big manufacturing data. He proposed an optimized state prediction deep neural network model based on Gauss-Bernoulli Deep Boltzmann Machine (GDBM). GDBM first uses Gaussian neurons to normalize the sequence input. Then, the extreme value perturbation and simple particle swarm optimization (tsPSO) method are introduced to optimize the model hyperparameters. Finally, he adopted the hybrid improved Liu-Storey Conjugate Gradient (MLSCG) algorithm to obtain a better convergence rate, thereby making the prediction process more computationally efficient (Wang et al. 2018). Yang HP introduced a digital double test bed in the environment of cyber physics and manufacturing systems. The physical environment is based on a custom production line that includes 3D printers, machine tools, inspection machines, robot processors, and buffers. The network environment of the test bed includes three-dimensional visualization of the line and several data analysis models. The digital double test bed connects the physical environment and the network environment through two interfaces (Yang et al. 2020). Wang W believes that in human–robot collaboration tasks, the performance of robot path planning directly affects the process of robot-to-human switching, and even the quality of collaboration. He presented an evaluation study of multi-robot path planning with different indicators and revealed their advantages and disadvantages in a typical human–machine collaborative manufacturing environment. Then, based on the proposed metric, he defined a cost function for the dual-arm robot to select the most efficient optimal path planning solution for its human partners in human–robot collaboration. He applied the proposed evaluation and optimization methods to multiple real human–robot collaborative manufacturing environments (Wang et al. 2020). Soualhi M believes that today, advanced industrial robots are being used more and more, and gradually replacing human activities for intelligent manufacturing that requires high precision and high performance. In this process, the slight deviation of the robot axis will cause the drift of other axes, which will significantly affect the quality of the product. Therefore, he aims to propose an effective method for monitoring and diagnosing the position deviation of the origin of a multi-axis robot. The proposed method uses encoder measurements for each axis to extract features and establish appropriate health indicators. These obtained health indicators are then injected into the machine learning classifier to locate the source of the deviation, that is, the axis that causes these drifts. In addition, the performance of the method was verified by an actual industrial test bed used for processing, which investigated the severity of various deviations on different axes of the robot (Soualhi et al. 2020).

The so-called key success factors refer to the key tasks that influence the successful realization of the corporate strategy. The key success factor method is to identify the key success factors and point out the key information set needed to achieve the goal, thereby determining the priority of system development. Generally speaking, in different business activities, the key success factors are different because of environmental factors, industry factors, corporate characteristics, and industry characteristics. This article considers the actual environment faced by manufacturing enterprises in the context of intelligent manufacturing and establishes a mathematical model of the mixed-flow assembly line balance problem with the production tact and the standard deviation of the workstation load as the objective function and increases the location and area constraints of the process to make the model more in line with the actual production situation. In view of the problem that there is no current research on the combination of assembly line balance and logistics scheduling, this paper uses the existing logistics scheduling system of the assembly workshop and draws on the relevant ideas of the dynamic scheduling strategy of the workshop to design a model of coordinated optimization of assembly line balance and logistics scheduling.

2 Methods and experiments

2.1 Data mining

The functional hierarchy is shown in Fig. 1. The business planning layer mainly involves various business activities required for manufacturing management. It reflects the management's thinking in the planning area, mainly including sales and service, production planning, inventory management, etc., most of the data information is in a static state. Real-time requirements are relatively low. The business planning layer generally uses an ERP system. From the top, we undertake the production task plan planned by the business planning layer and from the bottom to issue various production control instructions to the process control layer. The manufacturing execution layer can realize production process monitoring, equipment management, job scheduling and material tracking through MES. The process control layer mainly receives various production process execution instructions from the manufacturing execution layer and realizes the perception, monitoring and control of the actual physical bottom layer.

The planning layer (ERP) emphasizes the flexibility, planning, real-time and adaptability of enterprise business management, taking market demand, orders, inventory, etc., as the source of the plan, making full use of various internal resources, reducing production costs, and improving production efficiency; manufacturing execution layer (MES) emphasizes the execution and control of the plan and organically combines the business layer and the control layer of the production site through MES.

The MES functional system model is shown in Fig. 2. The production management model is the core part of MES, including 9 relatively independent sub-function modules. The functional modules in the production management model interact. By obtaining data from the business planning layer, information is transferred and reorganized between the production modules, sent to the

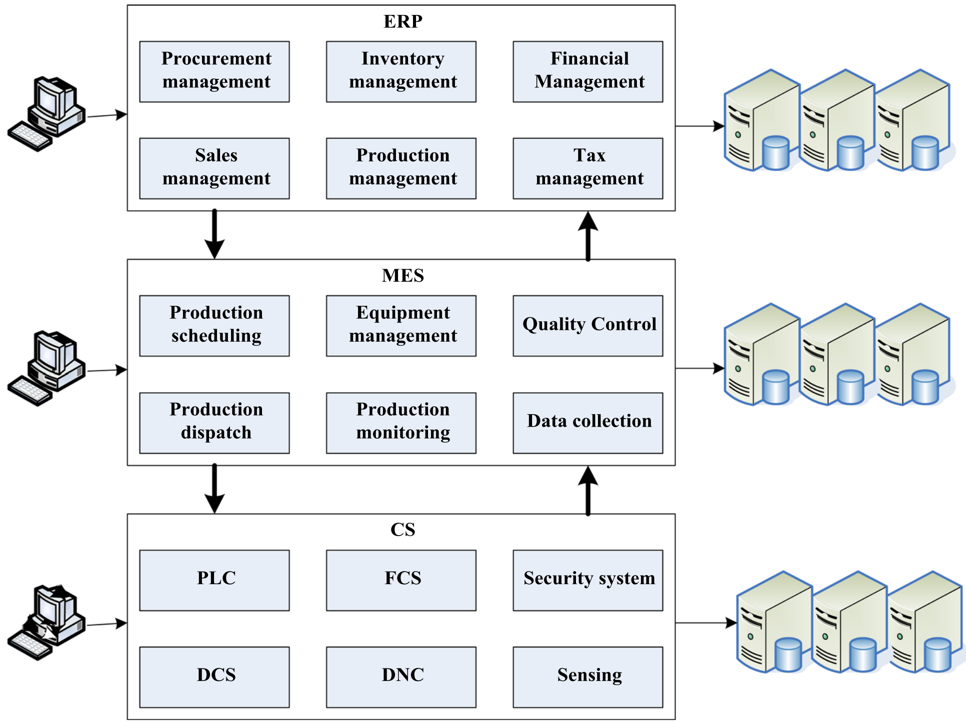

Fig. 1 Functional hierarchy division

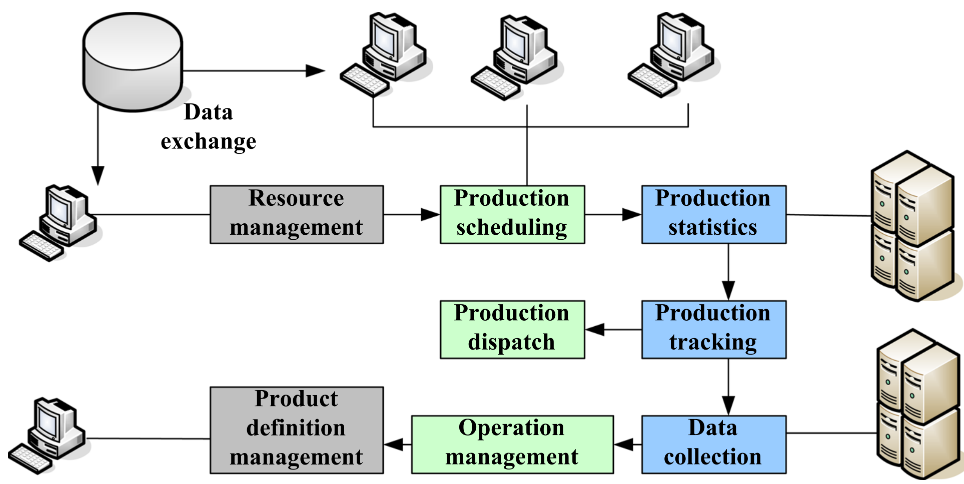

Fig. 2 MES functional system model

process control layer, and at the same time receiving the production feedback data of the process control layer. The statistical analysis of information data is fed back to the business planning layer. Maintenance management maintains the machinery and equipment personnel of the manufacturing execution layer to ensure the completion of the basic elements of the manufacturing execution layer. Quality management makes the manufacturing results more reasonable and standardized and ensures the quality and effectiveness of the manufacturing results. Inventory management is the starting point and focus of the manufacturing process. It is the supply of raw materials and the destination of finished products. Through inventory management, the smooth flow of resources in the manufacturing process is ensured. Other functional models that affect production are not necessary or applicable modules for all manufacturing companies, but they can also have a very important impact on production, or can provide useful assistance to production. For different manufacturing systems, the functions of the model are often different.

As a key component of the MES, the intelligent manufacturing real-time monitoring system can maintain the two-way communication capability between the planning management layer and the workshop control layer, realize the information exchange between the upper-level planning management system and the bottom-level process control system, and integrate production and management combining organically; it can effectively solve the problems of information islands and information gaps that appear in the process of manufacturing informatization.

The methods of how to "share" their respective experiences among multiple agents are as follows (Herwan et al. 2018):

$$Q_t(a) = \frac{\tilde{Q}_t(a) * \tilde{k}(a) + \hat{Q}_t(a) * \hat{k}(a)}{\tilde{k}(a) + \hat{k}(a)} \tag{1}$$

where $Q_t(a)$ is the Q value function of an agent,$\tilde{Q}_t(a)$ is the Q value function of the agent's independent learning and updating,$\hat{Q}_t(a)$ is the number of updates learned by the agent independently, $\hat{Q}_t(a)$ is the average Q value learned by all other agents, and $\hat{k}_t$ is the total number of updates for all other Agent learning. The gradient descent method adjusts the parameter vector of each sample in a small range, and the adjustment direction is the direction that can minimize the sample error. The expression is as follows (Smirnov et al. 2020):

$$MES(\overline{\theta}_t) = \sum_{s \in S} P(s)[V^{\pi}(s) - V_t(s)]^2 \tag{2}$$

$$\vec{\theta}_{t+1} = \vec{\theta}_t - \frac{1}{2}\alpha \nabla_{\vec{\theta}_t}[V^{\pi}(s_t) - V_t(s_t)]^2 \tag{3}$$

The general gradient descent method for state value prediction is as follows (Guest and Editorial, 2019):

$$\vec{\theta}_{t+1} = \vec{\theta}_t + \alpha[V_t - V_t(s_t)]\nabla_{\vec{\theta}_t} V_t(s_t) \tag{4}$$

The process operation time of a variety of products that can be assembled in a mixed-flow assembly line is different, and the market demand within the same production planning cycle is also different. Therefore, the operation time of each process in the integrated operation priority relationship of the mixed-flow assembly line needs to consider the operation time and operation time of each product. Production ratio during the planning period. According to market demand, the calculation process of the proportion of each type of product is as follows (Ji et al. 2021):

$$q_m = \frac{Q_m}{Q}\left(\sum_{m=1}^{M} q_m = 1\right) \tag{5}$$

In the formula, M is the number of product types in demand; q_m is the proportion of the number of m-th products; Q is the sum of the number of demand for M products.

Assuming that there are N assembly processes in the comprehensive work priority relationship diagram of a mixed-flow assembly line, the work time of each process in the comprehensive work priority relationship is calculated as follows (Moamin et al. 2020):

$$t_i = \sum_{m=1}^{M} q_m t_m \beta_{mi} \tag{6}$$

In the formula,t_i is the operating time of the i-th process in the mixed-flow assembly line; t_{mi} is the operating time of the m-th product process i; β_{mi} is whether the m-th product contains process i. In the second type of balance problem of mixed-flow assembly line, the size of the beat can be expressed by the balance rate of the assembly line. When the process operation time and the number of workstations are unchanged, it can be seen that the maximum balance rate of the assembly line also means the minimum production beat. Therefore, the objective function can be converted to maximize the assembly balance rate (Collins 2020).

$$f_1' = \max E = \frac{\sum_{i=1}^{N} t_i}{K \cdot CT} = \frac{\sum_{i=1}^{N}\sum_{m=1}^{M} q_m t_m \beta_{mi}}{K \cdot CT} \times 100\% \tag{7}$$

In the formula, CT is the production cycle of the mixed-flow assembly line; E is the balance rate of the mixed-flow assembly line; K is the number of mixed-flow assembly line workstations. In view of the fact that the balance of the mixed assembly line is a combinatorial optimization problem, there may be situations where the optimal solution is not the only one. In order to make the mathematical model more in line with the actual situation, this paper adds the objective function of minimizing the workstation load standard deviation, as follows (Qian et al. 2020):

$$f_2 = \min\sqrt{\frac{\sum_{j=1}^{K}(CT - T_j)^2}{K - 1}} \tag{8}$$

In the formula, Tj is the sum of the operating time of all processes in the j-th workstation in the mixed-flow assembly line. Considering the random fluctuation of the operation time, the operation time of each process in the integrated operation priority order of the mixed-flow assembly line is calculated as follows:

$$\mu_i = \sum_{m=1}^{M} \beta_{mi} q_m \mu_{\mathrm{mi}} \tag{9}$$

$$\sigma_i^2 = \sum_{m=1}^{M} \beta_{mi} q_m \sigma_{\mathrm{mi}}^2 \tag{10}$$

In the formula, μ_i is the average operating time of process i in the mixed-flow assembly line; σ_i^2 is the operating time variance of process i in the mixed-flow assembly line;μ_{mi} is the average operating time of the m-th product process i; σ_{mi}^2 is the m-th product process i Work time variance (Brito et al. 2020). Assuming that the j-th workstation contains V operation procedures, and there are K workstations in the mixed-flow assembly line, the operation time of each workstation in the mixed-flow assembly line is calculated as follows:

$$\mu_{\mathrm{j}} = \sum_{i=1}^{V} \mu_{ji}, \sum_{j=1}^{K} V_j = N \tag{11}$$

$$\sigma_j^2 = \sum_{i=1}^{V} \sigma_{\mathrm{ji}}^2 \tag{12}$$

where μ_{j} is the average operating time of workstation j in the mixed-flow assembly line; σ_{j}^2 is the operating time variance of workstation j in the mixed-flow assembly line; $\mu_{\mathrm{j}i}$ is the average operating time of process i in the j-th workstation in the mixed-flow assembly line; σ_{ji}^2 is the mixed-flow assembly line variance of the operation time of process i in the j-th workstation in Lu et al. (2020). Minimize the production cycle and minimize the standard deviation of the workstation load as follows:

$$F1 = \min CTs = \max_{1 \le j \le K} \left(\sum_{i=1}^{V} \sum_{m=1}^{M} q_{sm} \beta_{mi} \mu_{jmi} + \sqrt{\sum_{i=1}^{V} \sum_{m=1}^{M} q_{sm} \beta_{mi} \sigma_{jmi}^2} \Phi^{-1}(1-\alpha) \right) \tag{13}$$

$$F2 = \min SDIs = \sqrt{\frac{\sum_{j=1}^{K} \left[CTs - \left(\sum_{i=1}^{V} \sum_{m=1}^{M} q_{sm} \beta_{mi} \mu_{jmi} + \sqrt{\sum_{i=1}^{V} \sum_{m=1}^{M} q_{sm} \beta_{mi} \sigma_{jmi}^2} \Phi^{-1}(1-\alpha) \right) \right]^2}{K-1}} \tag{14}$$

In the formula, *CTs* is the production beat of the mixed-flow assembly line under the sth demand plan; *SDIs* is the standard deviation of the workstation load of the mixed-flow assembly line under the sth demand plan (Aricha, et al. 2021). The objective function of minimizing the production cycle can still be expressed by maximizing the balance rate, as follows:

$$F1' = \max Es = \frac{\sum_{j=1}^{K} \left(\sum_{i=1}^{V} \sum_{m=1}^{M} q_{sm} \beta_{mi} \mu_{jmi} + \sqrt{\sum_{i=1}^{V} \sum_{m=1}^{M} q_{sm} \beta_{mi} \sigma_{jmi}^2} \Phi^{-1}(1-\alpha) \right)}{K \cdot CTs} \tag{15}$$

In the formula, *Es* is the assembly balance rate of the mixed assembly line under the sth demand plan (Ding et al. 2020). The velocity of the particle is used to update the position information of the particle, which is the trend of the change of the position information. The initial velocity of the particle is defined as follows:

$$V_i = V_{\min(i)} + (V_{\max(i)} - V_{\min(i)}) * rand(1, N) \tag{16}$$

In this paper, the λ factor is introduced to make the individual learning coefficient and the group learning coefficient change nonlinearly. The expression of the λ factor is as follows:

$$\lambda = e^{-3\frac{i}{iter\max}} \tag{17}$$

In the formula, i is the current iteration number (Godor et al. 2020).

2.2 Work measurement process

After dividing the assembly processes of the two types of reducers, in order to ensure the authenticity and accuracy of the algorithm solution, this paper carries out the statistics of the assembly process operation time of the reducer according to the standard process of operation measurement and obtains true and reliable data. According to the actual process operation situation, this paper chooses the zero-return method in the stopwatch time research method to measure the process operation time of the reducer. The calculation formula of standard operating time is as follows:

$$t_s = t_n(1+\alpha) = t_o\theta(1+\alpha) \tag{18}$$

In the formula, t_s is the operating time of the standard process; t_n is the operating time of the normal process; t_{o} is the operating time of the observation process (Hauder et al. 2021). This paper selects the triple standard deviation method to check and analyze the observed data and find the average $\overline{X}$ and standard deviation σ of each group of data in a certain operating unit, the normal value is a number within $\overline{X} + 3\sigma$, and the value outside the range is excluded. The approximate state value function is as follows:

$$V_t(s) = \vec{\theta}_t^T \vec{\varphi}_s = \sum_{i=1}^{n} \theta_t(i)\varphi_s(i) \tag{19}$$

Update formula of parameter vector (Váncza et al. 2020):

$$\vec{\theta}_{t+1} = \vec{\theta}_t + \alpha\left[v_t - \sum_{i=1}^{n} \theta_t(i)\varphi_s(i)\right]\vec{\varphi}_s \tag{20}$$

2.3 System function design

The system mainly includes five sub-function modules, which are order management, material management, mixed-flow assembly line balancing, assembly line logistics scheduling and system management. Order management and material management are the basis for the operation of the system, providing parameter input for the balance of the assembly line and logistics scheduling; the balance of the mixed assembly line is the core function of the system, and the intelligent algorithm written by MATLAB is used to balance the mixed assembly line and optimize the assembly plan of the workstation. Displayed to the front end of the system, it reflects the intelligent characteristics of the production control system for intelligent manufacturing; the assembly line logistics scheduling is based on the balance result of the mixed assembly line, and the balance result is used as the task sequence input of the logistics scheduling, which optimizes the operational efficiency of the logistics system (AGV the driving path and running time); system management includes user management, system introduction and usage guide.

2.4 Database design

According to the analysis of system requirements, this paper designs the data table, which mainly includes two types of static data table and dynamic data table. The order information table, the material information table, the station status information table, and the product priority order relationship and time information table provide parameter input for the balance of the mixed-flow assembly line. After the optimal workstation job distribution plan is obtained, the assembly process information table is matched according to the assembly process information table. The assembly process information and calculation results of each station are also used as the basis of logistics scheduling. After the logistics scheduling is completed, the name of the material that each AGV needs to be transported can be obtained according to the AGV transport material information table, which is convenient for the selection of materials and further improves the operation of the entire workshop efficient.

2.5 Development environment

The development of this system is mainly composed of front-end technology, back-end technology, and front-end and back-end interaction technology. The front-end interface design is mainly completed by the Windows Forms application in C#; the front-end and back-end interactions are mainly realized by programming in the various controls of the form application; the back-end technology is the core content of the system, mainly including C#. NET and MATLAB Hybrid programming and C# connect to SQL Server database these two key technologies.

2.6 System operation process

After entering the system first, select the products to be processed according to the production order and the status of the workstation and convert the foregoing content into algorithm parameters for input. Material information and logistics scheduling are based on the result of assembly line balance. If abnormal disturbance occurs in the production process, the assembly line will be rebalanced and the logistics scheduling will be re-directed so that the assembly workshop can make self-decision and self-adaptation.

3 Results

Enterprises consume a large amount of coal with electricity, so coal consumption can be used to evaluate the effect of energy-saving resources. The energy consumption statistics of 5000-ton enterprises include 60 enterprises with an annual energy consumption of more than 10,000 tons and 4 "thousand enterprises" with an annual energy consumption of more than 180,000 tons. In 2017, 95 key industrial energy-consuming enterprises, including enterprises with 10,000 tons and a total energy consumption of 16.7155 million tons of standard coal, increased by 17.72% year-on-year; cumulative energy consumption totaled 70,921 million tons of standard coal, an increase of 24.15% year-on-year; total industrial energy consumption of 10,000 yuan comprehensive energy consumption of output value was 585.21 kg of standard coal/10000 yuan, an increase of 11.42% year-on-year. The comprehensive energy consumption of 600,000-ton enterprises totaled 565.13 million tons of standard coal, a year-on-year decrease of 0.54%; the comprehensive energy consumption of 10,000 yuan of industrial output value was 496.62 kg of standard coal per 10,000 yuan, a year-on-year decrease of 5.45%. In 2017, the energy consumption of the output

Table 1 Output value and energy consumption of key industrial energy-consuming enterprises in the city in 2017

Name	Unit	Enterprises with more than 5,000 tons	Enterprises with more than 10,000 tons	Enterprises above 180,000 tons
Number of households	–	95	60	4
Total energy consumption	10,000 tons of standard coal	1671.55	1390.39	876.77
Comprehensive energy consumption	10,000 tons of standard coal	709.21	565.13	225.06
Comprehensive energy consumption per 10,000 yuan of industrial output value	Kg of standard coal(ten thousand yuan)	585.21	496.62	846.78

value of the city's key industrial energy-consuming enterprises is shown in Table 1.

Through the design and development of a real-time monitoring system for intelligent manufacturing, on the one hand, the business information of the planning management layer is detailed and decomposed, and the formed operation instructions are issued to the underlying process control layer; on the other hand, the actual process of control and the operating status of the equipment are tracked in real time. Real-time collection, processing, calculation and analysis of on-site data information, timely processing of real-time events and feedback to the plan management.

In 2017, the city's 99 key industrial energy-consuming enterprises had a total energy consumption of 16.2103 million tons of standard coal, a year-on-year decrease of 2.76%; the cumulative energy consumption was 6.901 million tons of standard coal, a year-on-year decrease of 3.6%; the comprehensive energy consumption of the total industrial output value of 10,000 yuan 552.1 kg of standard coal per 10,000 yuan, a year-on-year decrease of 5.67%. The comprehensive energy consumption of 600,000-ton enterprises totaled 5,428,600 tons of standard coal, a year-on-year decrease of 3.94%; the comprehensive energy consumption of 10,000 yuan of industrial output value was 458.9 kg of standard coal per 10,000 yuan, a year-on-year decrease of 7.56%. Table 2 shows the energy consumption of the output value of key industrial enterprises in the city in 2017.

Through the intelligent manufacturing real-time monitoring system, the full integration of the enterprise planning layer and the process control layer is realized, the information communication problem between the upper planning system and the lower control system is solved, and the integration, intelligence and agility of workshop production management are realized. The plan is to build a bridge between the management and the underlying control, fill the gap between the two, and solve the bottleneck of the "information island" and "information gap" in the implementation of the manufacturing industry and its informatization development.

By 2018, the total energy consumption of 99 key industrial energy-consuming enterprises in the city was 14.861800 tons of standard coal, a year-on-year decrease of 7.61%; comprehensive energy consumption totaled 5,716,500 tons of standard coal, a year-on-year decrease of 17.16%; the total industrial output value of 10,000 yuan was comprehensive energy consumption of 458.9 kg of standard coal per 10,000 yuan, a year-on-year decrease of 5.43%.

The total energy consumption of 600,000-ton enterprises was 12.226 million tons of standard coal, a year-on-year

Table 2 Output value energy consumption of key industrial enterprises in the city in 2017

Name	Unit	Enterprises with more than 5,000 tons	Enterprises with more than 10,000 tons	Enterprises above 180,000 tons
Number of households	–	99	60	4
Total energy consumption	10,000 tons of standard coal	162 1.03	1348.96	828.0
Comprehensive energy consumption	10,000 tons of standard coal	690.1	542.86	212.1
Comprehensive energy consumption per 10,000 yuan of industrial output value	Kg of standard coal(ten thousand yuan)	552.1	458.9	804.37

Table 3 Energy consumption of output value of key industrial energy-consuming enterprises in the city in 2018

Name	Unit	Enterprises with more than 5,000 tons	Enterprises with more than 10,000 tons	Enterprises above 180,000 tons
Number of households	–	99	60	4
Total energy consumption	10,000 tons of standard coal	1486.18	1222.62	799.65
Comprehensive energy consumption	10,000 tons of standard coal	571.65	432.79	199.65
Comprehensive energy consumption per 10,000 yuan of industrial output value	Kg of standard coal(ten thousand yuan)	458.9	431.2	855.18

decrease of 9.19%; the total energy consumption of 600,000-ton enterprises was 4.3279 million tons of standard coal, a year-on-year decrease of 17.33%; the comprehensive energy consumption of the total industrial output value of 10,000 yuan was 431.2 kg standard coal/10,000 yuan, a year-on-year decrease of 6.04%. Table 3 shows the output value and energy consumption of key industrial energy-consuming enterprises in the city in 2018.

As a bridge of information interaction between the upper-level planning management system and the bottom-level process control system, the intelligent manufacturing system solves the problems of information islands and information gaps faced by the manufacturing industry. With the rapid development of computer software and hardware and information technology, intelligent manufacturing systems are developing toward standardization and unification in terms of architecture, functional modules and information interaction.

Aiming at the problem of industrial process data transmission in the Internet environment, a communication protocol and data packet scheduling rules are designed, the encapsulation format and meaning of different types of data packets are specified, and different priorities are set for data packets. On the one hand, it is guaranteed the sudden information is notified to the client in time, and on the other hand, the amount of data information transmission is simplified. At the same time, the usage rules and application steps of the communication protocol are explained in detail.

In 2019, the city's 99 key industrial energy-consuming enterprises had integrated energy consumption of 5,233,100 tons of standard coal, a year-on-year decrease of 8.2%; the comprehensive energy consumption of 10,000 yuan of industrial output value was 448.36 kg of standard coal/10000 yuan, a year-on-year decrease of 5.43%. The comprehensive energy consumption of enterprises in 2019 is shown in Table 4.

This chapter studies and analyzes the theoretical basis of the intelligent manufacturing real-time monitoring system and the key technologies required for system implementation. First, it introduces the information flow transmission process of the intelligent manufacturing execution system; then, in order to improve the efficiency and stability of data transmission, it introduces the basic concepts, working principles, characteristics, application process, etc., of related data scheduling algorithms.

The comprehensive energy consumption of 600,000-ton enterprises totaled 3,952,800 tons of standard coal, a year-on-year decrease of 8.67%; the comprehensive energy consumption of 10,000 yuan of industrial output value was 401.19 kg of standard coal/10000 yuan, a year-on-year decrease of 6.96%. In 2020, the energy consumption of the

Table 4 Comprehensive energy consumption of enterprises in 2019

Name	Unit	Enterprises with more than 5,000 tons	Enterprises with more than 10,000 tons	Enterprises above 180,000 tons
Number of households	–	99	60	4
Total energy consumption	10,000 tons of standard coal	1472.31	1237.87	807.47
Comprehensive energy consumption	10,000 tons of standard coal	523.31	395.28	187.33
Comprehensive energy consumption per 10,000 yuan of industrial output value	Kg of standard coal(ten thousand yuan)	448.36	401.19	995.48

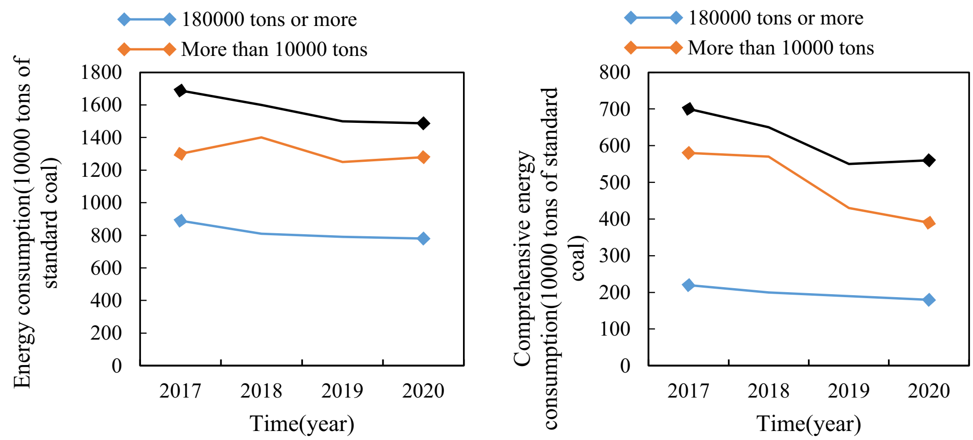

Fig. 3 The output value and energy consumption of the city's key industrial energy-consuming enterprises in 2020

Table 5 Regional energy consumption of key industrial energy-consuming enterprises in the city in 2018

Category	Industrial output		Comprehensive energy consumption	
	100 million yuan	Year-on-year increase or decrease (%)	10,000 tons of standard coal	Year-on-year increase or decrease (%)
Area A	126.48	2.54	88.28	1.28
Area B	99.88	7.05	20.38	− 10.23
Area C	263.09	7.93	59.14	− 13.86
Area D	220.82	− 7.19	29.62	− 5.14
Area E	26.32	6.57	145.49	− 1.91
Area F	251.42	− 12.91	81.37	− 10.08

output value of the city's key industrial energy-consuming enterprises is shown in Fig. 3.

In 2018, the regional energy consumption of key industrial energy-consuming enterprises in the city is shown in Table 5. The total energy consumption of each district and city accounted for the proportion of 95 key industrial energy-consuming enterprises in the city. The top 5 areas are Zone A, Zone B, Zone C, Zone D and Zone E, with the proportions being 36.25, 16.00, 10.00, 9.46 and 8.63%; the top five districts and cities in terms of comprehensive energy consumption are District B, District D, District E, District C and County F, with the proportions being 20.52, 17.42, 12.45, 11.47 and 11.07%, respectively. It can be seen that area A is the area with the most energy consumption, and area B is the area with the most comprehensive energy consumption.

Limited by the middleware, especially when the data transmission frequency is relatively fast, the real-time access of the acquisition module and the monitoring module to the middleware is prone to deadlock, and the real-time performance of the data transmission process cannot be guaranteed. Aiming at the problems that occur in the process of information interaction in the transfer method, the direct sending method is used to realize the information transmission between the acquisition module and the monitoring module, which avoids the phenomenon of deadlock and improves the real-time nature of information interaction. However, when the amount of data is large or the transmission time slice is small, the first-come, first-served communication method is used to transmit the data.

The total energy consumption in Zone C varies with the year as shown in Fig. 4. It can be seen from the figure that from 2016 to 2019, the total energy consumption and comprehensive energy consumption of production in C district have shown a downward trend year by year. In 2019, compared with 2012, they decreased by 18.69 and 24.72%, respectively.

The construction of a management information system is a socio-technical system project that costs a lot, lasts for a long time, is technically complex, and involves a wide range of aspects. Scientific planning can reduce the blindness of system development and construction, and avoid the waste caused by the failure of information system construction to achieve the expected results. Scientific planning makes the various subsystems have good integrity and scalability, and avoids the lack of unified planning

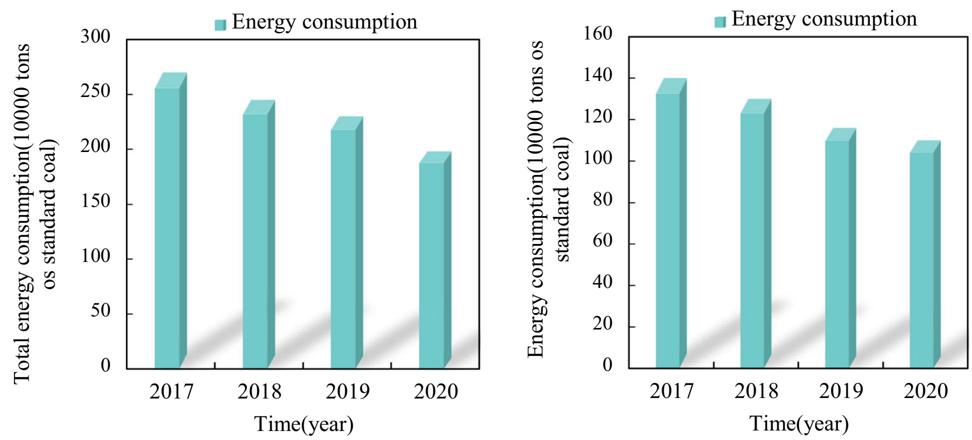

Fig. 4 The total energy consumption in Zone C varies with the year

between systems, resulting in the lack of integration between systems and the formation of information islands.

City M has always attached importance to the construction of energy-saving economy and has made remarkable achievements in the construction of energy-saving economy during the Eleventh Five-Year Plan period. The samples for this study are mainly taken from large, medium and small manufacturing companies in M City. Under the pressure of energy conservation economy, these manufacturing enterprises have either started the strategic transformation of energy conservation, or are facing the environmental pressure of strategic transformation. The questionnaire was filled in by the middle and above management members (chairman, general manager, deputy general manager and some of the department managers) of the enterprises actually surveyed. The survey sample is shown in Fig. 5.

In order to fully understand the company's awareness of energy-saving resources, a survey was conducted on the company's internal management personnel. An in-depth investigation of the reasons for the implementation of energy-saving resources was conducted. For energy-saving resource project subsidies, managers accounted for 15%, agreed sales accounted for 40%, and agreed that labor productivity has a little relationship accounted for 45%. The results of the survey of internal management personnel of the enterprise are shown in Fig. 6.

The acquisition of production parameter data mainly comes from the secondary calculation based on the initial data. The production material parameters and production output data mainly come from the enterprise resource planning system of the research object M company. The acquisition of environmental factors mainly comes from the weather database in the Internet. The market factors mainly come from the relevant national statistical information publishing websites, and the energy price factors and actual energy consumption data come from the energy management department of the target company M. The company's input of raw materials for each material is shown in Fig. 7.

The forging branch of M company is mainly divided into forging working group and free forging working

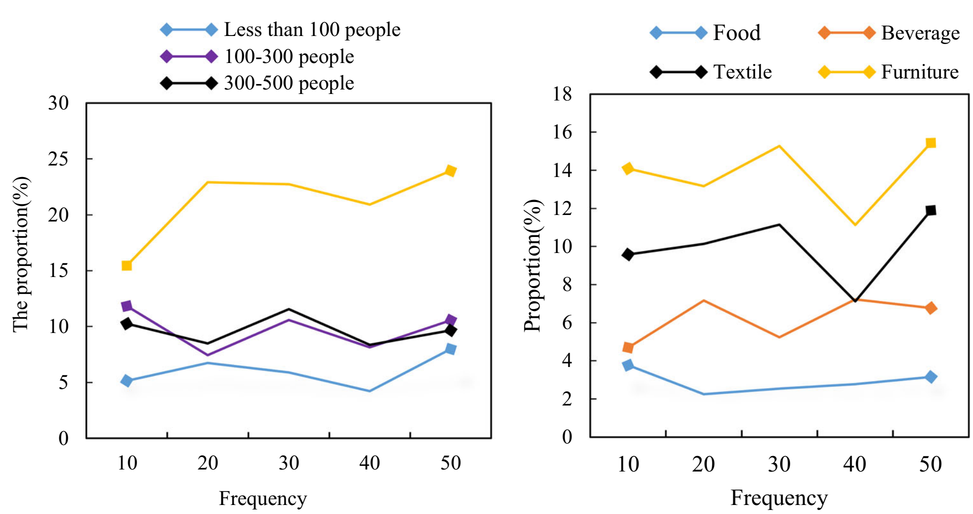

Fig. 5 Survey sample

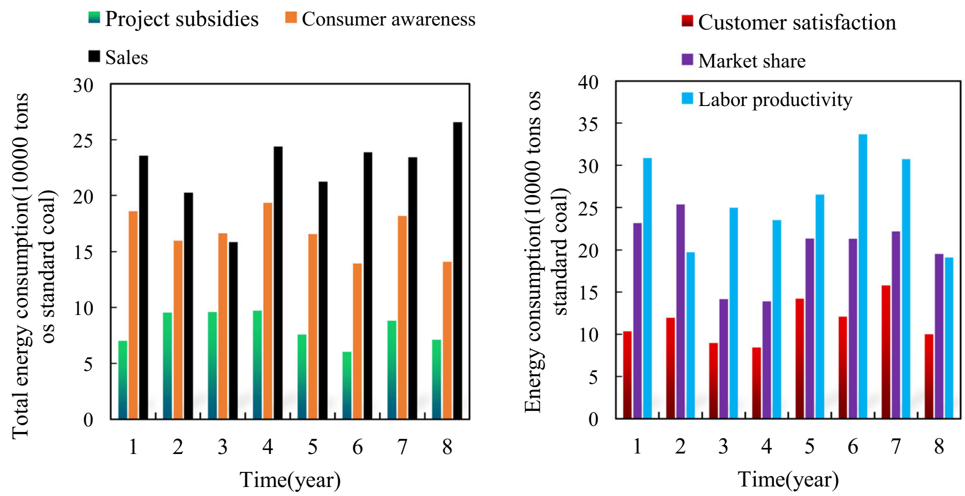

Fig. 6 Survey results of internal management personnel of the enterprise

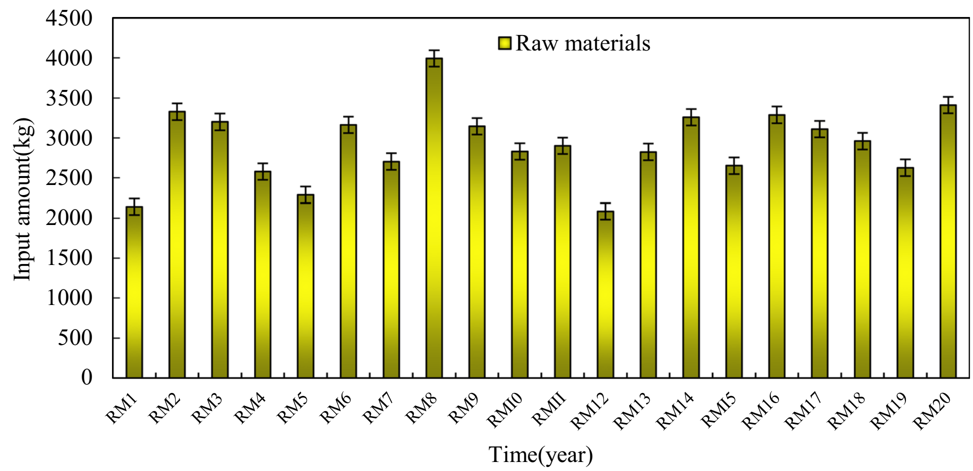

Fig. 7 The company's input of raw materials for each material

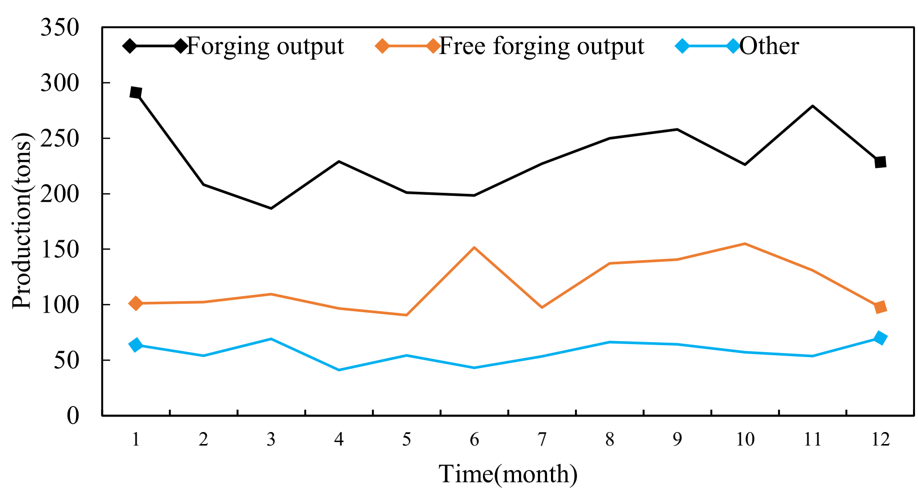

Fig. 8 One year's output of M company's forging branch

group, which are divided according to the striking energy of the main production tools forging hammers. The die forging working group is mainly divided into 25 kJ working group, 80 kJ working group, 125 kJ working group, 400 kJ working group: the free forging working group is mainly divided into 30 kJ free forging working group, 175 kJ free forging working group, and 350 kJ free forging working group. The annual output of the forging branch of company M is shown in Fig. 8.

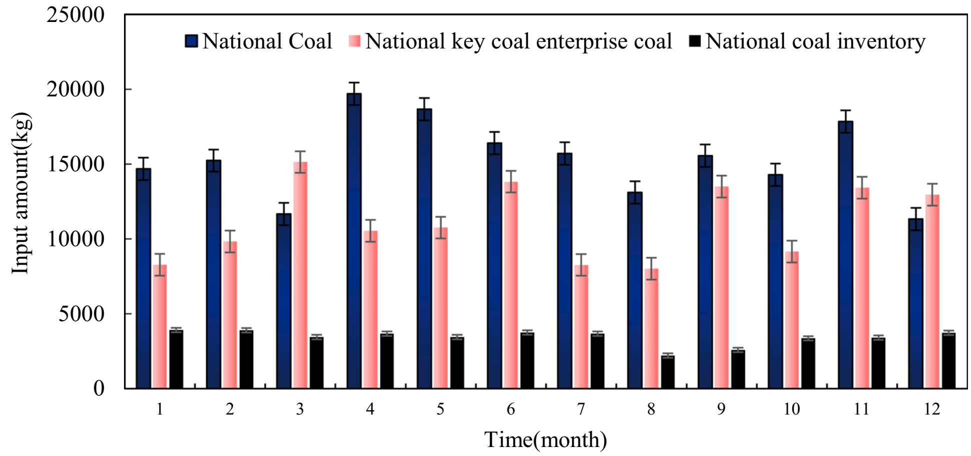

Fig. 9 National coal production, national key coal enterprise coal production and national coal inventory

Historical output, historical inventory and historical prices of related products (X11, X12, X13): According to the characteristics of company M's sales products, the target company for its products is the coal production and manufacturing industry. According to the characteristics of this industry, it is announced with the National Coal Industry Network. According to the data, X11 uses the historical production of coal products, X12 uses the historical inventory of coal products, and X13 uses the Coal Price Index (BSPI) and the China Coal Price Index (CCPI) to measure, the national coal production, the national key coal enterprise coal production national coal inventory is shown in Fig. 9.

The energy consumption data come from the statistics of the energy management center of M company. Since the relocation of M company to the new industrial park in early 2019, the energy consumption composition of the forging branch has undergone significant changes. All water use, including tap water, is recycled. The loss is very small, so the energy consumption statistics mainly include the consumption of electricity and natural gas. The consumption of electricity and natural gas from January 2019 to December 2019 is shown in Fig. 10.

4 Discussion

The primary driving force for energy conservation in manufacturing enterprises is economic benefits. The choice of appropriate energy-saving methods can enable manufacturing enterprises to obtain an optimal profit, reduce the tight constraints of resources and the environment on manufacturing enterprises, and improve the competitiveness of manufacturing enterprises. From the perspective of research content, the existing literature mainly focuses on the energy-saving service company industry market and energy-saving service company development analysis. Although a small amount of literature involves the choice of energy-saving methods, compared with the important role of energy-saving management in enterprise management, the research content is slightly insufficient. From the perspective of research objects, more researchers are studying the industry market of energy-saving service

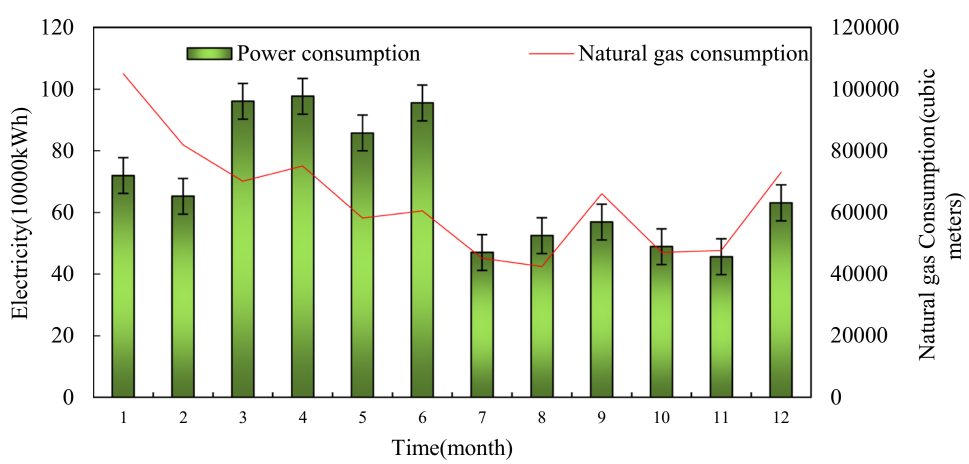

Fig. 10 Electricity and natural gas consumption

companies, the development of energy-saving service companies, and the operation of energy-saving service companies from the perspective of energy-saving service companies, and they rarely analyze another aspect of contract energy management. Important energy-saving main body energy-saving enterprises, such as manufacturing enterprises. However, it is difficult to change the situation of manufacturing enterprises as the main body of energy-saving in China for a long time. It can be seen that there is an urgent need to change the research object and consider this issue from the perspective of energy-saving enterprises. From the perspective of research methods and research perspectives, most energy-saving method selection studies use qualitative or empirical methods to compare various energy-saving methods from a macro-perspective and lack the application of quantitative analysis methods to explore the best of manufacturing companies from a micro-perspective. The optimal energy-saving method selection decision is manifested in the few quantitative models that are relatively simple and do not involve enterprise production and operation, customer consumption behavior, financing, risk, market structure, and so on. Since the operation strategy, consumer behavior, and market structure of the enterprise may affect the choice of energy-saving methods of the manufacturing enterprise, it can be seen that compared with the actual needs, it is necessary to change the research perspective from the macro to the micro and to make a certain degree of innovation in research methods. The contribution of this article lies in the construction of energy-saving methods that include key factors such as enterprise production operations (such as extending the dynamic economic batch model to enterprise energy-saving methods), customer consumer behavior (such as considering pricing factors), and market structure from the perspective of energy-saving enterprises. The method of selection model is used to study the decision-making problem of energy-saving mode selection of manufacturing enterprises (Wei et al. 2020; Hamdi et al. 2019).

Manufacturing enterprises need a truly comprehensive data center that can manage data unification, data version consistency and many other aspects. The production of manufacturing enterprises has many departments, and the cooperation between purchasing, inventory, sales and production departments is not close enough. If the customer order changes, the production plan cannot keep up with the change at any time, and the materials purchased by the purchaser cannot keep up with the change at the same time. If the supply of raw materials cannot keep up with the change, timely supply may lead to the shutdown of the production line. Therefore, if it can have independent, changeable and flexible raw material management, it is an urgent demand for factory operations (Lunelli and Cecconello 2019).

In primitive manual production, BOM errors may occur, leading to errors in production technology (MPS). The factory estimates the exact quantity of materials based on the BOM. Purchasing or production processing is the prerequisite for generating the plan. However, the outdated method often has the phenomenon of more or less requisition, so it is inevitable that BOM budget errors will cause unnecessary consumption of materials. Especially for outsourcing orders, if the company outsources the production materials, the BOM is not refined, and the entrusted party may make money. Therefore, optimized BOM and implementation of lean production are important directions of factory reform. Both the production department and the raw material purchasing department want to make longer-term production plans, but in a market economy, orders are ever-changing. If you want to adapt to changes in orders, the result will inevitably lead to changes in the production plan (Dutton 2019).

Changing personnel, changing bills of materials, and changing raw material purchases may lead to the suspension of production lines. The most terrible thing for companies is the suspension of production lines. Therefore, the production and operation of enterprises are facing adapting to this rapidly changing era. Due to the rapid growth of the company, the outdated management model has not adapted to the status quo of the company. The previous management of BOM, the formulation of production plans, the purchase of raw materials, the sales of the sales department, the incoordination between various departments, and the information and data are not communicated. Information islands and decentralization of management. In traditional paper-based management, the original data are always distributed in thousands of documents, and there is no predictability of the market, so it is unable to cope with the competition among fiercely competitive enterprises.

The production scheduling receives the main production plan of the business planning layer and generates specific production scheduling information according to the product characteristics and production requirements and existing material resources and sends it to the production dispatching module. After the production dispatching module receives the production dispatching information, it is based on the current equipment operation status and time sequence are assigned to the operation management module, and the operation management module finally issues production instructions to the process control layer. During the production dispatching period, the dispatching information will be sent to the production tracking module, and then fed back to the production dispatching, forming a closed-loop dispatching control. At the same time, the data of the production tracking module are used as feedback information to compare with the pre-planned information. Make corresponding adjustments to plans that are inconsistent with reality. Including the specific requirements of equipment and work orders to re-prioritize production, improve equipment utilization, and rationally arrange equipment production to equally share machine load. Production scheduling must fully consider limited time, equipment and material resources to meet target production requirements (Coatney 2019).

The emergence of mixed-flow assembly line promotes the transformation of manufacturing enterprises focusing on assembly production from traditional single variety production to multi-variety, small batch production mode and improves the ability of enterprises to respond to market demand. Assembly line balancing and logistics scheduling is assembly workshop, two key problems need to solve the uncertainty of demand uncertainty and assembly time mixed-flow assembly line balancing and dynamic balancing an assembly line and logistics scheduling collaborative optimization, and control of assembly shop production line balance and logistics scheduling, meet the assembly manufacturing enterprises for the development of intelligent manufacturing since the decision, adaptive, etc. It is of great theoretical significance and application value to improve the efficiency of enterprises and their ability to respond rapidly to market demand changes and realize sustainable production and development (Li et al. 2019).

5 Conclusion

Resource allocation and integration capabilities have a positive impact on strategic transformation and have a significant positive impact on vision transformation and organizational transformation in strategic transformation. The ability of resource allocation and integration itself includes the cultivation of strategic resources by the enterprise to adapt to environmental changes, and the integration of resources in accordance with the principle of resource hierarchy and acceptability to achieve the purpose of reasonable resource structure and high allocation efficiency. Therefore, in the context of low-carbon economy, manufacturing companies re-allocate corporate resources rationally by identifying changes in the external environment and assessing their impacts. The resources of an enterprise include not only soft resources, such as vision, but also hard resources, such as human resources, and so on. Manufacturing companies integrate these into corporate visions through the identified low-carbon economic construction and consumer environmental protection concepts and then transform them into specific corporate behaviors.

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Data availability Data sharing does not apply to this article because no data set was generated or analyzed during the current research period.

Declarations

Conflict of interest The authors declare that they have no competing interests.

Ethical standards This article is ethical, and this research has been agreed.

Consent to participate This article is ethical, and this research has been agreed.

Consent for publication The picture materials quoted in this article have no copyright requirements, and the source has been indicated.

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