European Journal of Business, Economics & Management

Vol. 1 No.2 2025

Article Open Access

Data-Driven Process Improvement Methods and Results Sharmg

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Received: 11 May 2025
Revised: 16 May 2025
Accepted: 29 May 2025
Published: 03 June 2025

Abstract: With the continuous advancement of data-driven technology, enterprises are gradually realizing the intelligence and optimization of processes in production and management. This paper deeply discusses the process optimization strategy based on data-driven methods and shares the resulting achievements, analyzes how the Internet of Things and edge computing improve production efficiency, how machine learning and visual recognition enhance quality control, how intelligent energy management reduces energy consumption costs, and how intelligent decision support systems optimize management efficiency. Through the application of these advanced technologies, not only has the production efficiency of enterprises been improved, but costs have also been effectively controlled, promoting the in-depth development of digital transformation.

Keywords: data-driven; Internet of Things; machine learning; intelligent decision-making

1. Introduction

In the context of digital transformation, data-driven approaches have brought new possibilities for enterprises to enhance efficiency and improve management. The previous approach of relying on manpower and experience for management is no longer suitable for high-speed and precise requirements. Therefore, many enterprises have adopted data-driven approaches to improve business processes, aiming to enhance production efficiency and reduce operating costs. However, in practical operation, how to efficiently integrate these technologies and integrate them into production activities remains a core issue that urgently needs to be solved [1]. This article will delve into how these technologies are integrated into enterprise business processes and share their achievements in improving efficiency, reducing costs, optimizing decision-making, and demonstrating the enormous potential of data-driven improvement.

2. Overview of Data-Driven Approach

Data-driven refers to the efficient allocation and management of resources through the collection, evaluation, and utilization of large-scale real-time data to support decision-making and business guidance. Traditional business decisions often rely on subjective experience, intuition, or professional judgment, lacking scientific data support, which often appears outdated and imprecise in rapidly developing market environments. And data-driven analysis is based on real data, analyzing various details in business processes and using intelligent means to make precise adjustments to decisions, thereby significantly enhancing the overall operational efficiency of enterprises. Data-driven optimization applies across multiple business levels, including production and manufacturing, quality monitoring, energy control, and customer service. Therefore, data-driven improvement not only means technological innovation, but also an important driving force for enterprises to shift from traditional operating methods to intelligent and detailed management models. This transformation requires enterprises to comprehensively upgrade their hardware facilities, data processing skills, and technological applications, providing solid support for the accuracy of decision-making and operational efficiency [2].

3. Data Driven Process Improvement Methods

3.1. Improvement of Intelligent Data Collection Technology

The application of intelligent data collection technology is the starting point and foundation for data-driven process improvement. Modern intelligent data collection technology enables real-time, continuous, and complete capture of data through IoT devices, smart sensors, and automation systems. Enterprises install diverse sensors on their production lines to track key parameters such as temperature, humidity, pressure, flow rate, and machine operation status. These sensors instantly send captured data to cloud servers or local data systems through wireless or wired networks, and complete preliminary data organization and purification through specific software to ensure the accuracy and effectiveness of the data. The preliminary organized data is then transmitted to the data storage and analysis system [3]. During this process, the data analysis model combines real-time monitoring mechanisms to conduct detailed analysis of the collected information, to identify abnormal conditions in the production process in real time. For example, when an abnormal increase in device temperature is detected, the system will calculate the critical value for fault warning according to a specific algorithm:

$$T_{threshold} = T_{normal} + \Delta T_{critical} \quad (1)$$

Among them, $T_{threshold}$ is the fault alarm threshold for equipment temperature, T_{normal} is the temperature at which the device operates normally, $\Delta T_{critical}$ is the temperature change caused by equipment failure. When the temperature exceeds the threshold, the alarm mechanism will automatically activate, issuing a check prompt to the operator to prevent system failure. Advanced data collection methods can be integrated with the production command system to enable data-driven monitoring of the production process. Dynamic data not only reveals the operational status of equipment, but also provides information on production speed, material usage, and process parameters, helping management to make decisions quickly. Enterprises can use this information to adjust production strategies and improve production arrangements [4].

3.2. Machine Learning Driven Quality Control

Machine learning–driven quality control methods promote the intelligence of quality management by extracting patterns from large amounts of production data. The starting point of this process is the collection of data. Enterprises need to accumulate key real-time information from various stages of production, including machine operation status, raw material types, temperature and humidity of the production environment, and other factors. These data will then be input into machine learning models to train and improve algorithm performance. Algorithms will analyze past data and construct quality prediction models, such as predicting factors that may affect product quality in different scenarios based on production parameters (such as temperature, pressure, rate, etc.). The model can make real-time predictions on data from various stages and provide warnings for potential quality issues. As production activities continue, algorithms will continuously incorporate new data to improve the accuracy of predictions. This technology can also be integrated with online quality inspection equipment to implement real-time monitoring of products on the production line. By integrating visual, acoustic, and other detection systems, the system can promptly identify surface defects and dimensional deviations, notifying operators in real time [5]. As shown in Table 1, the quality control process driven by machine learning can be divided into several stages, each involving different data types and application scenarios.

Table 1. Quality Control Process Driven by Machine Learning.

Stage	Data type and content	Application scenarios and functions
data acquisition	Equipment status, production parameters (such as temperature, humidity, speed, etc.)	Collect real-time data from various production processes to ensure comprehensive data coverage and provide a foundation for subsequent analysis
Data Processing and Modeling	Historical production data and quality fluctuation records	Establish a quality prediction model using historical data, identify quality influencing factors, and optimize algorithms
Real-time monitoring and analysis	Real time production data and testing results	Conduct quality inspection and prediction for each production process, automatically identify potential problems and issue warnings
Adjust production process	Production data, model output	Adjust production parameters based on real-time analysis to ensure stable and consistent product quality

3.3. Intelligent Energy Management and Energy Saving Technologies

Enterprises can dynamically monitor and optimize energy consumption through advanced information technologies such as the Internet of Things, cloud technology, and big data processing. The primary step in intelligent energy management is to use high-precision sensors and intelligent energy meters to collect consumption information of various energy sources. These sensors will synchronize real-time collected data to the cloud or local servers, building a complete energy consumption information database. Subsequently, energy management software will process and analyze this data to evaluate the energy usage status at each stage of production, identify peak and valley energy consumption, and identify potential waste areas [6]. For areas with significant energy waste, the system can automatically generate improvement suggestions or directly adjust energy usage patterns. In order to track energy consumption more accurately and optimize energy configuration, the system uses specific algorithms to calculate the energy consumption ratio of each link:

$$\mathrm{E}_{ratio} = \frac{\mathrm{E}_{actual}}{\mathrm{E}_{\max}} \times 100\% \tag{2}$$

Among them, E_{ratio} is the energy consumption ratio, E_{actual} is the actual amount of energy consumed, $\mathrm{E}_{\max}$ is the maximum allowable energy consumption for this stage. If the energy consumption ratio exceeds the predetermined upper limit, the system will trigger an alert and guide operational adjustments to prevent unreasonable energy consumption. The application of energy-saving technology is not only about regulating and controlling energy consumption, but also involves improving production processes. The system can make subtle adjustments to the production mode and reduce unnecessary energy consumption by analyzing the direction of energy in the production process. The system can also predict future energy consumption based on production arrangements, thereby achieving optimized management of energy procurement and distribution, ensuring higher efficiency and better economy in energy utilization.

3.4. Intelligent Decision Support and Management Optimization

The Intelligent Decision Support System (DSS) gathers rich real-time and historical data to assist managers in achieving more accurate and rapid decision-making processes. This process first requires integrating multiple data sources into a unified platform, covering production line dynamic monitoring data, machine operation status, inventory data, market dynamics, and other information. After the data integration is in place, the system will launch data analysis software for advanced data mining, using pattern recognition technology and prediction algorithms to conduct real-time analysis and evaluation of current production activities, supply chain links, and market trends. During this process, the auxiliary decision-making system continuously gathers various new information and automatically adjusts the decision-making algorithm to continuously improve the accuracy and response speed of decision-making. At the same time, the system keeps up with changes in production conditions, updates resource allocation plans in real time, and ensures the smooth implementation of production arrangements. If there is a delay in a certain stage of production, the system will immediately provide feedback and replan resource allocation such as raw material procurement and inventory mobilization to prevent unnecessary loss of resources due to changes in production pace.

4. Achievement Sharing of Data-Driven Process Improvement

4.1. Internet of Things and Edge Computing Improve Production Efficiency

Combined with the Internet of Things (IoT) and edge computing technology, the data monitoring, processing and decision-making capabilities of the production link have achieved a leap in intelligence and efficiency. By installing IoT sensors on key parts of the production line and production equipment, enterprises can real-time grasp the working status, process indicators, environmental temperature and humidity, flow rate, and many other information of the equipment. Edge computing technology further enhances the speed and accuracy of data processing, can complete preliminary data analysis at the edge nodes of the production site, and reduces dependence on remote cloud. In case of equipment failure or production efficiency reduction, edge computing can respond immediately and adjust production steps, effectively preventing further decline in production efficiency. The edge computing system can detect early signs of machine failures in real time and proactively dispatch maintenance personnel to prevent production line downtime caused by equipment issues. The integration of the Internet of Things and edge computing provides more accurate data support for production scheduling [7]. The system can predict potential production bottlenecks by tracking real-time production line operating parameters, and automatically adjust production pace or improve resource allocation. To sum up, the application of IoT technology and edge computing has greatly enhanced the adaptability and response speed of the production line, helped enterprises to use resources more efficiently, reduced idle time, and thus comprehensively improved production efficiency.

4.2. Machine Learning and Visual Recognition Enhance Quality Control

The combination of machine learning and visual recognition technology has driven innovation and breakthroughs in the field of quality control. With the help of machine intelligence and computer image processing, enterprises are able to achieve highly automated and precise quality inspection processes. The imaging system on the production line can capture product images in real-time at each stage, and then conduct in-depth analysis of the appearance features and dimensional details of the products through deep neural network technology. These intelligent algorithms can learn from past production data, distinguish subtle differences between qualified and unqualified products, and thus achieve automatic identification and quality assessment of individual products. The application of machine intelligence technology has greatly improved the intelligence level of quality control. After training on massive production data, these intelligent models can gain insights into key variables that affect product quality, such as environmental temperature, humidity changes, equipment vibration, etc., and make predictive analyses based on them. For example, once the model detects that environmental conditions during the production process exceed preset upper or lower thresholds, it will immediately trigger an alarm, prompting operators to take corresponding measures. These algorithms can also automatically adjust control parameters based on real-time collected production data to ensure the sustained stability of product quality [8]. This type of quality monitoring system, which integrates machine intelligence and image recognition technology, not only significantly improves detection accuracy but also greatly enhances efficiency, reduces human errors, and ensures that every product meets the established quality requirements.

4.3. Intelligent Energy Management Reduces Energy Consumption Costs

The application of intelligent energy management systems significantly reduces the energy consumption costs of enterprises. Faced with the gradual increase in energy demand from industrial production, optimizing energy efficiency has become a core element in enhancing the core competitiveness of enterprises. By utilizing intelligent means, enterprises can dynamically monitor energy consumption, and through detailed data analysis, accurately identify energy consumption peaks, inefficient links, and energy waste links, and then implement targeted optimization measures. This system integrates IoT technology to collect real-time energy consumption data in various production processes, creating a comprehensive energy monitoring and management platform. The system has the function of real-time tracking of device energy consumption and can predict future energy demand based on production arrangements, thereby achieving proactive resource adjustment. The system can identify the high energy consuming parts in the production process through in-depth analysis of previous data, and then propose improvement measures. The system utilizes automatic adjustment of energy usage strategies to effectively reduce energy consumption. For example, intelligent power management systems have the ability to monitor power loads in real-time and intelligently allocate power resources based on the working status of machines. When the equipment operates at low load, the system will automatically reduce power output; conversely, when the equipment load increases, the system ensures stable power output. The intelligent energy management system not only helps enterprises achieve detailed management of energy consumption, but also significantly reduces energy consumption costs and enhances the economic benefits of enterprises by reducing waste and improving energy utilization efficiency.

4.4. Intelligent Decision Support System Enhances Management Efficiency

Traditional management decisions often rely on experience and historical data, while intelligent decision support systems provide more objective and real-time decision-making basis through data mining and analysis. As shown in Figure 1, the architecture of the intelligent decision support system mainly includes three levels: data integration and collection layer, data analysis and modeling layer, and decision support and optimization layer.

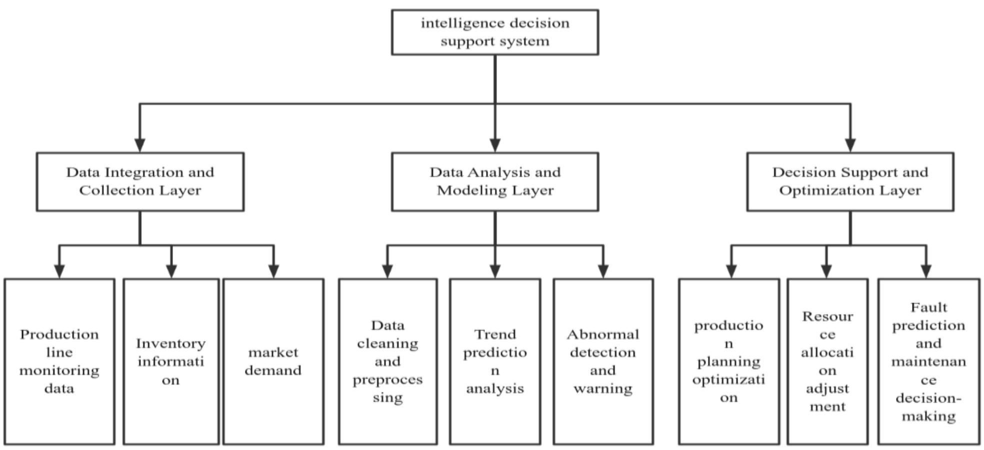

Figure 1. Architecture Diagram of Intelligent Decision Support System.

The system collects and analyzes real-time data from various aspects of the enterprise, forming an efficient decision support system that enables managers to make precise decisions in multiple fields such as product production, logistics distribution, and warehouse control. The key advantage of this intelligent decision support system lies in its excellent data processing skills. This system can conduct detailed analysis of real-time information generated in the production process, and can also rely on past data to make forward-looking predictions on future trends, helping enterprises discover possible risk points and business opportunities. For example, the system can predict the production demand for the next few months, and based on this, plan the configuration of raw materials in advance to prevent an imbalance between production supply and demand; The system can also analyze the frequency of equipment failures during operation, providing a basis for equipment maintenance and updates, thereby reducing the negative impact of equipment failures on the production process. The decision-making intelligent system has the ability to adjust production plans in real-time based on market dynamics and production progress. When encountering unexpected situations in the production process, the system can immediately notify the management and automatically optimize the production plan, involving the replanning of raw material allocation and human resources. With this flexible decision support, enterprises can improve production efficiency, reduce inventory costs, and thereby enhance management efficiency. The application of intelligent decision support systems not only improves the decision-making speed and accuracy of managers, but also promotes the optimization of management modes through data-driven approaches, enhancing the comprehensive competitiveness of enterprises.

5. Conclusion

Through data-driven optimization methods, enterprises can achieve comprehensive upgrades in production efficiency, quality supervision, energy conservation, and management decision-making. The Internet of Things and edge computing technology optimize the production process, machine learning and visual recognition improve the accuracy of quality detection, intelligent energy management effectively reduces energy consumption costs, and intelligent decision support systems enhance the decision-making ability and response speed of enterprises. The data-driven optimization strategy not only enhances the level of production automation and intelligence, but also endows enterprises with greater profit potential and stronger market competitiveness. In the future, with the advancement of technology, data-driven optimization strategies will be widely implemented in various industries, injecting stronger impetus into the sustained growth of enterprises.

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