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Designing Data-Based Production Systems to Improve Productivity and Product Quality

Abstract

The development of digital technology, the Internet of Things (IoT), and data analytics have driven a major transformation in the production systems of the manufacturing industry. Companies are required to be able to increase productivity while maintaining product quality to remain competitive in the era of global competition. One effective approach is to design a data-driven production system, which is a system that leverages real-time production data to support fast, accurate, and evidence-based decision-making. This article discusses the concept, design stages, and benefits of implementing a data-based production system in improving operational efficiency and quality control. This system includes the process of collecting data from machines and operators, data processing using analytical software, to visualizing information in the form of dashboard monitoring. The results of the conceptual study show that data-based production systems are able to reduce waste, reduce product defects, shorten lead times, and significantly increase labor productivity. The integration of digital technology and automation is a key factor in realizing an adaptive and sustainable production system.

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1. Introduction

The manufacturing industry is currently facing increasingly fierce competition dynamics due to globalization, technological developments, and changes in consumer preferences that are taking place very quickly. Customers demand not only competitive prices, but also high product quality, diverse product variety, and shorter delivery times. This condition forces companies to continue to innovate in their production systems to be able to adapt flexibly and respond to changes in market demand. Conventional production processes, with manual data collection and slow evaluations, often lead to delays in decision-making and inaccurate identification of problems in the field. As a result, waste of raw materials, waiting time, overproduction, and defective products are still the main challenges that hinder the improvement of operational performance.

To answer these challenges, companies need to optimize the production process as a whole with a systematic and evidence-based approach. One of the increasingly relevant solutions is the implementation of a data-driven production system, which is a system that utilizes real-time production data as well as statistical and computational analysis to support faster, more accurate, and objective decision-making. Through this system, every production activity can be recorded and analyzed in an integrated manner, ranging from machine performance, production cycle time, equipment utilization rate, energy consumption, to labor performance. The collected data not only serves as a historical report, but also as a basis for performance evaluation, production planning, and continuous improvement [1].

Data-driven production systems include a variety of critical components, such as sensors and Internet of Things (IoT) devices for automated data collection, Manufacturing Execution System (MES) systems for controlling production processes, and analytics software to process and visualize information in the form of interactive dashboards. With real-time monitoring of engine performance, companies can detect potential breakdowns early through a predictive maintenance approach, so that downtime can be minimized. In addition, material flow analysis allows the identification of bottlenecks or process bottlenecks that cause production delays. In terms of quality, product inspection data can be analyzed using statistical methods such as Statistical Process Control (SPC) to ensure that the process remains within control limits and reduce the level of product defects.

This approach is in line with the concept of Industry 4.0 which emphasizes the integration of digital technology, big data, artificial intelligence, and automation systems in the manufacturing environment. Through this integration, the production system becomes more transparent, adaptive, and digitally connected. The information obtained from data analysis can be used to conduct production simulations, capacity planning, and dynamic production schedule optimization. Thus, the company is not only able to improve labor productivity and resource use efficiency, but also maintain the consistency of product quality in the long term.

Overall, the implementation of a data-driven production system provides strategic benefits for manufacturing companies. In addition to being able to reduce waste and improve operational efficiency, this system also supports more objective and measurable fact-based decision-making. In the long run, the transformation towards a data-driven production system will strengthen the company's competitiveness in the global market, while opening up opportunities for the development of sustainable and innovative intelligent manufacturing [2].

2. Materials and Methods

2.1. System Approach and Design

This paper uses a conceptual approach and system design approach to develop a data-driven production system model that aims to improve productivity and product quality in the manufacturing environment. This approach focuses on the integration of digital technology, production data management, and performance analysis methods as the basis for decision-making. The design is carried out systematically through the identification of system needs, the design of the data architecture, the selection of supporting technologies, and the development of a production performance evaluation mechanism.

The method used does not focus on one specific company, but rather describes a general framework that can be applied to the manufacturing industry with the characteristics of discrete and continuous production processes.

2.2. Materials and Data Sources

The main material in the design of this system is production data obtained from manufacturing operational activities. The data includes:

a. Machine performance data (operating time, downtime, production speed, Overall Equipment Effectiveness/OEE)
b. Material flow data (number of incoming materials, work in process, inventory, finished product)
c. Product quality data (number of defects, type of defects, rework rate, inspection results)
d. Workforce data (hours worked, productivity, work efficiency)
e. Cycle time, lead time, waiting time

Data sources come from digital production systems such as machine sensors, Internet of Things (IoT) devices, Enterprise Resource Planning (ERP) systems, Manufacturing Execution System (MES), and quality control records. In addition, theoretical references from academic literature and industry standards are used as a basis in designing performance indicators and analysis methods.

2.3. Data Collection Procedure

Data collection is carried out through a digital-based monitoring system that allows automatic and real-time data recording. IoT sensors and devices are installed on production machines to record operational parameters such as temperature, pressure, speed, and cycle time. Quality data is collected through an integrated inspection system, either manually or automatically using vision system technology.

Historical production data is collected for analysis as a comparison against actual performance. The data integration process is carried out through a centralized database that allows synchronization between production, warehouse, and quality control departments.

2.4. System Architecture Design

Data-driven production system architecture is designed in several layers, namely:

a. Data Acquisition Layer
   Collect data from machines, sensors, and other production systems.
b. Data Progressing Layer
   Analyze data using statistical methods, efficiency calculations, trend analysis, and predictive modeling.
c. Visualization and Decision Support Layer
   Presenting analysis results in the form of an interactive dashboard to support managerial decision-making quickly and accurately.

This design aims to create an integrated flow of information from the production floor to the management level.

2.5. Data Analysis Methods

Data analysis was carried out using quantitative approaches and descriptive analytics. Some of the methods used include:

a. Productivity Analysis, by calculating the ratio of output to labor input and production time.
b. Calculation of Overall Equipment Effectiveness (OEE) to measure machine effectiveness based on availability, performance, and quality rate.
c. Statistical Process Control (SPC) to monitor the stability of the production process and detect quality deviations.
d. Bottleneck analysis, to identify key bottlenecks in the production pipeline.
e. Trend and Predictive Analysis, to estimate potential machine breakdowns or spikes in production demand.

The results of the analysis are used as the basis for the formulation of strategies for continuous performance improvement and quality control.

2.6. System Performance Evaluation

The system evaluation was carried out by comparing performance indicators before and after the implementation of the data-based system. The main indicators analyzed include:

a. Increased workforce productivity
b. Reduced production lead time
c. Reduction of product defect rates
d. Decreased engine downtime
e. Efficiency of using raw materials

In addition, the evaluation also considers non-technical aspects such as the ease of use of the system, the speed of access to information, and its impact on management decision-making.

2.7. Validation and Continuous Improvement

To ensure that the system runs optimally, a data validation process is carried out periodically and system performance evaluation is carried out through internal audits. The continuous improvement approach is applied by utilizing the results of the analysis as a feedback loop to make system adjustments, improve analytical algorithms, and optimize the production process [3].

3. Discussion

The design of a data-based production system shows that the use of digital technology and data analysis is able to significantly increase productivity and product quality. With real-time monitoring and performance dashboards, companies can identify production bottlenecks, machine downtime, and quality deviations more quickly and accurately. The data-driven approach supports more objective decision-making, so that corrective actions can be taken in a timely and effective manner [4].

In terms of productivity, data analysis helps detect bottlenecks and optimize production schedules and machine maintenance. Meanwhile, in the quality aspect, the application of statistical control allows for early detection of product defects and process variations. This has an impact on reducing rework, scrap, and operational costs. Data transparency also improves coordination between operators and management, making processes more controlled and integrated [5].

However, the implementation of a data-based production system requires the readiness of technological infrastructure, investment in digital devices, and increasing the competence of human resources. The challenges of system integration and data security also need to be considered. Overall, data-driven production systems are in line with the concept of Industry 4.0 and have the potential to be the main strategy in improving efficiency, quality consistency, and competitiveness of manufacturing companies [6].

4. Conclusions

Data-based production system design is a strategic approach that is able to increase productivity and product quality in a sustainable manner. Real-time production data utilization, machine performance analysis, and statistical-based quality control enable companies to identify process bottlenecks, reduce waste, and make decisions faster and more accurately. This system supports the creation of a more efficient, controlled, and transparent production process.

In addition to improving output and quality consistency, data-driven systems also encourage a culture of continuous improvement through measurable performance evaluations. Integration with digital technologies such as IoT, automation, and advanced analytics strengthens the transformation towards smart manufacturing.

However, the success of implementation is highly dependent on the readiness of technological infrastructure, adequate investment, and the competence of human resources in managing and analyzing data. Therefore, companies need to implement this system in a planned and gradual manner, accompanied by ongoing training and management support, so that the benefits can be felt optimally and sustainably.

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