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QUALITY MONITORING AND OPTIMIZATION IN COMPUTER-INTEGRATED MANUFACTURING: A STUDY ON AI-DRIVEN DECISION SUPPORT SYSTEMS

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ABSTRACT

Quality assurance and process optimization have been transformed by the incorporation of AI into production processes. Improving manufacturing performance is the main emphasis of this study, which delves into the topic of AI-driven real-time monitoring and process improvement. With an emphasis on their use in industrial settings, the paper examines new developments in AI technology. The suggested system allows for the continuous monitoring of production parameters via the use of machine learning algorithms, sensor data, and IoT connection. Early defect diagnosis is made possible by the AI-driven architecture, which reduces the chance of interruptions and inferior performance. The study delves deeper into the ways AI may optimize industrial processes in real-time using analytics, adaptive control, predictive maintenance, and intelligent decision-making.

KEYWORDS: AI integration; process optimization; fault prognosis; efficiency enhancement; machine learning

INTRODUCTION

When machines and processes are automated, control systems are used to run them. Significant developments in industrial production, including milestones like continuous chemical production, industry robots, and the autonomous control of the steam engine, may be traced back to this. Computers and the use of information have become more important in automation due to the development of information technology. For processes like process control, product traceability, and handling capacity, modern companies often use several IT systems. Automation of data analysis has become more popular as businesses amass more and more data. New computer programs using so-called machine learning techniques are being created to improve data-based prediction and decision-making.

The goal of quality control is to make sure that the final goods are up to par with what the corporation or the consumers have specified. Nowadays, most industrial organizations rely on this fast expanding area that emerged in the second half of the twentieth century. It has more than one use: Bad components may be screened out before they reach the client by quantifying what matters to a product or component. It is also possible to regulate processes so that quality variations are less common, leading to improved quality and reduced expenses.
In recent years, Machine Learning has seen tremendous growth, with many IT companies using it to enhance search engines, voice recognition, and internet marketing. Uncertainty surrounds the obvious questions of where, when, and how to use software-based automation, which has the ability to unleash latent potential in the industrial business.

By consolidating design, planning, and control into one system, Computer-Integrated Manufacturing (CIM) has shook up the manufacturing business. Computer-aided manufacturing (CAM), computer numerical control (CNC), and computer-aided design (CAD) are just a few examples of the cutting-edge technology that CIM systems use to boost production quality, efficiency, and productivity.

The capacity to monitor and regulate production processes in real-time is one of the main advantages of CIM, which helps to enhance product quality. Nevertheless, with today's complicated production processes and ever-increasing expectations for high-quality goods, guaranteeing such items in CIM systems is no easy feat.
Because they allow manufacturers to identify and fix quality problems in real-time, quality monitoring and optimization are essential parts of CIM systems. This reduces the risk of faulty items and improves overall product quality. Measurement precision, surface smoothness, and material attributes are just a few of the critical quality metrics that may be monitored via the use of sensors and other data collecting technology. In contrast, optimization makes use of sophisticated algorithms and statistical models to sift through high-quality data in search of enhancement possibilities. No CIM system is complete without quality monitoring and optimization. To survive in today's cutthroat industrial market, organizations need to crank out high-quality goods at a rapid pace. Companies may lose a lot of money, have their reputations tarnished, and even hurt customers because of defective goods.

LITERATURE REVIEW

Lee (2012) highlighted the role of smart manufacturing systems leveraging IoT and machine learning for real-time quality optimization. Their study proposed a predictive framework integrating sensor data with machine learning models to detect defects and improve efficiency in computer-integrated manufacturing (CIM).

Tao et al. (2014) explored the integration of digital twin technologies with IoT-enabled manufacturing frameworks. Their research demonstrated how virtual simulations, combined with real-time IoT data, enhance predictive quality control and reduce production downtime.

Wang (2015) analyzed the application of deep learning models in computer-integrated manufacturing for quality monitoring. They proposed a hybrid IoT and machine learning framework that integrates image recognition technologies for defect detection in production lines.

Zhang (2016) developed a cloud-based quality management system that uses IoT devices for data collection and machine learning for decision-making. Their study emphasized scalability and adaptability in managing complex manufacturing workflows.

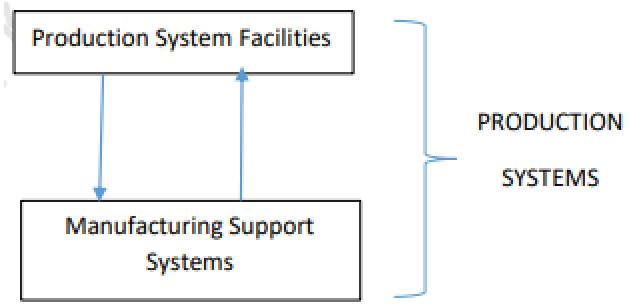
Sharma (2017) focused on a holistic integration of machine learning algorithms with IoT for optimizing production quality in CIM systems. The study introduced an adaptive learning framework for predictive maintenance, ensuring consistent product quality.

COMPUTER INTEGRATED MANUFACTURING

The term "Computer Integrated Manufacturing" (CIM) refers to a production process that uses specialized software to manage every step of the product lifecycle. Data needed for different tasks is seamlessly transferred from one program to another. For instance, design is when product data is developed. Without losing any information, this data must be moved from the modeling program to the production program. To connect the automated parts of a factory or production facility with the design and manufacturing processes, CIM makes use of communication technologies and a single database whenever possible. Removing the time-consuming, money-sucking, and error-prone human element from production is what CIM is all about. CIM is an acronym for "complete improvement management," which refers to a systematic and all-encompassing strategy for enhancing the performance of a manufacturing firm. Automation is a constantly evolving technology because of how dynamic it is. Substituting automated machinery for human workers is what this term refers to. Production may be operated and controlled via the use of automation technology, which focuses on mechanical, electrical, electronic, computer, hydraulic, and pneumatic systems. Systems for production: A company's manufacturing activities are carried out by a combination of People, Equipment, and Procedures known as a production system.

It is divided into the following 2 categories:

1. Production system facilities
2. . Manufacturing support systems



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NATURE AND ROLE OF THE ELEMENTS OF CIM SYSTEM

- Marketing
- Product Design
- Planning
- Purchase
- Manufacturing Engineering
- Factory Automation Hardware
- Warehousing
- Logistics and Supply Chain Management
- Finance
- Information Management

Figure 2 shows the nine main components of a CIM system, which are,

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