

IoT Real-Time Production Monitoring and Automated Process Transformation in Smart Manufacturing

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ABSTRACT

Conventional automobile manufacturing plants involve intricate assembly, testing, and debugging processes heavily reliant on manual operations. This study aims to explore the application of industrial internet of things (IIoT) and deep learning algorithms to achieve process automation in manufacturing. Firstly, utilizing IIoT technology, OPC UA, and point cloud fitting techniques, a comprehensive modeling of most equipment and materials within the factory is conducted, constructing a digital twin (DT) model as a virtual representation of actual equipment. Subsequently, the study innovatively introduces the deep Q network algorithm, facilitating the automatic transition of the production process and improving production efficiency. Through comparison with ten baseline models, the proposed model demonstrates an improvement in production efficiency of at least four percentage points compared to other models. Experimental validation confirms the effectiveness of the proposed model in the smart factory for electric vehicle manufacturing.

KEYWORDS

Digital Twin, DQN, IIoT, Process Automation, Smart Factory, Smart Manufacturing

INTRODUCTION

The establishment of intelligent factories has emerged as a significant global trend in the manufacturing sector, aimed at enhancing production efficiency, reducing costs, and achieving more flexible and sustainable manufacturing processes through the adoption of advanced technologies and digital solutions. Illustrative construction cases, such as the intelligent manufacturing transformation implemented by China's Haier Corporation, which involved technologies like the Internet of Things (IoT), cloud computing, and big data analytics, have resulted in the development of intelligent home appliance manufacturing facilities. This intelligent factory construction project has elevated the flexibility and adaptability of production lines, facilitated customized manufacturing, reduced product time-to-market, and strengthened market competitiveness. The process automation of electric

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vehicle manufacturing factories is currently a highly prominent research direction in the intelligent manufacturing landscape (Bathla et al., 2022). The investigation into this technology encompasses various aspects such as the enhancement of factory production efficiency, optimization of production resource utilization (Zhang & Dilanchiev, 2022), and the promotion of environmentally friendly manufacturing (Yang et al., 2022). First, it is poised to significantly enhance production efficiency. Traditional automotive manufacturing plants involve intricate assembly, testing, and debugging processes heavily reliant on manual operations. The introduction of automation technologies (Li et al., 2022b), such as robots and intelligent assembly lines, can substantially reduce the time devoted to manual operations and elevate the operational efficiency of production lines. The improvement in production efficiency aids in reducing manufacturing costs, facilitating quicker and more flexible production responses to rapidly changing market demands. Secondly, it is expected to contribute to the improvement of the quality and consistency of electric vehicles (Jiménez-Ramírez et al., 2023). Given the intricate nature of the components and systems in electric vehicles, errors during manufacturing can result in a decline in product quality. The introduction of automated processes can mitigate human errors and variations, ensuring more precise manufacturing and consequently enhancing overall product quality and consistency. Thirdly, it holds the potential to reduce energy consumption (Salman et al., 2022) and carbon emissions (Kumar et al., 2022). Automation technologies enable the optimization of production processes, precise control of energy usage, and the reduction of unnecessary waste, thereby rendering the manufacturing process more environmentally friendly and aligning with the overall eco-friendly philosophy of electric vehicles. Fourthly, it aids in driving the digitization transformation of the manufacturing industry (Favoretto et al., 2022). Through the integration of advanced technologies such as intelligent manufacturing and big data analytics, production shop floors can achieve higher levels of digital management and monitoring. This not only facilitates real-time tracking of production processes and optimization of resource allocation but also enhances production efficiency through data analysis, providing a more scientifically grounded basis for business decision-making. Therefore, research into the automation of processes in electric vehicle manufacturing plants holds crucial reference value for a nation's industrial strategy formulation. With the increasing global attention on the electric vehicle industry, an in-depth investigation into the application of artificial intelligence technologies in electric vehicle manufacturing can provide robust support for the development of national industrial policies (Srivastava et al., 2022). On a global scale, this contributes to elevating a nation's industrial competitiveness and strengthening its technological leadership in the field of electric vehicles.

Currently, deep learning technology has found numerous applications in the automation of factory production processes (Tercan & Meisen, 2022), and these innovative applications have profound impacts on enhancing production efficiency (Salman et al., 2022), improving product quality, reducing costs, and driving digital transformation. Due to its capability to learn and comprehend vast amounts of production data, deep learning enables intelligent decision-making, resource optimization, and waste reduction through real-time monitoring and analysis of data on the production line, thereby achieving a higher level of production efficiency. Deep learning empowers production systems with autonomous learning and adaptability, fostering the progression of factories toward intelligent manufacturing. This enhances the autonomy and adaptability of production systems, reducing dependence on human intervention and achieving a more highly automated production process (Zhou et al., 2022a).

Given that deep learning technology allows real-time monitoring and control of product quality through the analysis of sensor data and image recognition, it is often utilized to predict potential quality issues, take preemptive measures, reduce defect rates, and enhance the stability of product quality. At the level of each module within a factory, deep learning technology holds significant potential in energy management subsystems. By intelligently adjusting equipment operation based on the analysis of energy usage data in the production process, the system can optimize energy utilization, reduce energy consumption, and achieve a more environmentally friendly and sustainable manufacturing process (Musbah et al., 2022).

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