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Deep Learning Driven by Digital Twins Helps the Development and Breakthrough of Adaptive Automated Production Lines

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ABSTRACT
With the acceleration of the transformation of manufacturing to intelligence and flexibility, the integration of digital twins and deep learning technologies has brought new development opportunities for adaptive automated production lines. This paper deeply analyzes the characteristics of digital twins in constructing virtual models and mapping physical entities in real time, as well as the advantages of deep learning in data processing, pattern recognition, prediction and decision making, expounds how the collaboration of the two enables production lines to realize self-perception, dynamic optimization, and intelligent decision making, and discusses the technology application path from multiple dimensions such as accurate modeling, real-time monitoring, fault prediction, and process optimization. The challenges and future trends are analyzed to reveal the key role of this cutting-edge technology portfolio in improving the adaptive capacity of the production line and promoting high-quality development of the manufacturing industry.

KEYWORDS
Digital twins; Deep learning; Adaptive production line; Intelligent manufacturing; Data-driven

1 Introduction

In today's highly competitive global manufacturing landscape, companies are pursuing higher production efficiency, superior product quality and rapid market response. As the core means to achieve these goals, adaptive automated production lines are gradually becoming the key direction of manufacturing upgrading. The digital twin technology realizes the bidirectional interaction and accurate mapping between virtual and reality by creating the digital mirror of physical entity. With a powerful neural network architecture, deep learning can deeply mine the value of data and make intelligent decisions. The organic combination of the two is like injecting strong impetus into the adaptive automated production line, opening a new chapter of development, and is expected to reshape the production mode and competitiveness pattern of the manufacturing industry.

2 Digital Twins: Virtual Building Blocks of Adaptive Production Lines

2.1 Digital Twins

Digital twin technology, originated in 1969 NASA Apollo program, then named "twin", mirror reflects the real-time state of the vehicle, this early twin is a physical entity[1-2]. The turning point came in 2003, when Professor Michael Grieves from the University of Michigan first proposed the concept of virtual digital expression and gave it a clear definition in his product life cycle management course. He described a method of using virtual means to represent actual facilities[2-5].

From 2003 to 2005, this concept was referred to as the "spatial model of mirrors"[3]. Subsequently, between 2006 and 2010, it was redefined as the "Information mirror model"[6-8]. In 2011, Michael Grieves and two NASA professors proposed the concept of "digital twins", and the term was first cited[2]. In 2014, Professor Michael Grieves published a white paper on digital twins. This white paper emphasizes that the digital twin conceptual model includes three main parts: physical products in real space, virtual products in virtual space, and connected data and information between the two[9-10]. In 2017, Zhuang Cunbo et al.[11] further elaborated the concept of digital twin technology and established the architecture of product digital twins. At the same time, they give the implementation of product digital twins in the product design stage, manufacturing stage and service stage, taking product innovation to a new level. In 2019, Professor Tao Fei and his research team[12] proposed the concept of a five-dimensional digital twin model, which includes five parts: physical entity, virtual entity, service, twin data and connection.

2.2 Real-Time Mapping and Interaction of Digital Twins in the Production Line

With the help of high-precision sensors, the digital twin enables accurate capture of the real-time status of the production line. The sensor collects equipment vibration, temperature, speed, and product size, shape, surface quality and other data at a high frequency, transmits it to the data layer for processing, and drives the virtual model to update in real time, ensuring that the virtual production line and the physical production line are highly synchronized in state and behavior. Operators or control systems can carry out process adjustment, equipment layout optimization and other operations in the virtual environment, and feed back to the physical production line through instructions, achieving two-way interaction between virtual and reality, greatly improving the efficiency and accuracy of production line debugging and optimization, and reducing trial and error costs. Figure 1 shows the automatic production line.

Figure 1 Automatic production line

3 Deep Learning: Intelligent Engine for Mining Production Line Data

3.1 Algorithm System and Advantages of Deep Learning

Deep learning consists of rich algorithms such as multi-layer perceptrons, convolutional neural networks (CNNS), recurrent neural networks (RNNS) and their variants. CNN is good at processing data with spatial structure, such as product images in production line visual inspection, automatically extracting image features through convolution layer, accurately identifying product surface defects, size deviations and other problems; RNN and its improved Long Short-term memory network (LSTM) and gated cycle unit (GRU) are suitable for processing time series data, analyzing equipment operation data according to time series, capturing the dynamic trend of equipment performance, and predicting potential faults. Compared with traditional machine learning, deep learning does not need to manually design complex features, and can automatically learn deep patterns from massive data to adapt to complex and changing production line conditions.

3.2 Deep Learning Helps Production Line Data Mining and Intelligent Decision-Making

In the massive and complicated data flood of the production line, deep learning is like a powerful intelligent engine, deeply mining the value of data, and driving the production line to a new stage of intelligent decision-making.

For the mining of product quality data, the quality prediction model built by deep learning plays a key role. A large amount of data related to product quality will be generated during the operation of the production line, including the characteristic parameters of raw materials, the process parameters of each production process and environmental factors. Through the comprehensive analysis of these multi-source data, the deep learning model builds a complex and accurate quality prediction model. For example, in the auto parts manufacturing line, the deep learning model can predict in advance whether the dimensional accuracy, mechanical properties and surface quality of the product meet the standard requirements according to the hardness and chemical composition of the steel, the temperature, pressure and time parameters of the process such as stamping and welding, as well as the environmental data such as the humidity and temperature of the workshop. Once it is predicted that the product may have quality problems, immediately intervene in the front end of production, adjust the process parameters or replace the raw material batches, control the generation of defective products from the source, greatly improve the product's primary pass rate and reduce production costs.

Big data running on analytical devices is another important application area of deep learning. By continuously collecting the operating parameters of the equipment under different working conditions, such as the speed, torque and current of the motor, the vibration frequency and amplitude of the bearing, as well as the water temperature and flow rate of the cooling system, the deep learning model can identify the mode characteristics of the equipment under different operating states, such as normal, sub-health and fault. Based on these feature recognition, the model can intelligently decide the maintenance timing and strategy of the equipment. Compared with the traditional periodic maintenance mode, this state-based predictive maintenance is more accurate and efficient. When the model determines that the equipment is about to enter the risk period of failure, timely maintenance warning is issued, and detailed maintenance suggestions are pushed, including the parts to be replaced and the operation steps of maintenance, etc. According to this, operation and maintenance personnel can prepare spare parts in advance and reasonably arrange the maintenance period to avoid the production line shutdown caused by sudden equipment failure, effectively reduce the maintenance cost and improve the availability of equipment. Extend the average failure-free time of the equipment to ensure the stable operation of the production line.

Deep learning can also integrate production process data to optimize scheduling decisions. In the complex production line system, the rational allocation of production tasks, the sequence optimization of material distribution and the cooperative scheduling of human resources are very important. Through deep learning of order demand, equipment capacity, material inventory, personnel skills and other comprehensive data, the deep learning model dynamically adjusts the production task allocation plan and material distribution order. For example, in the production line of consumer electronics, in the face of urgent order insertion or product model switching, the deep learning model can quickly re-plan the production process, prioritize high-capacity equipment to produce urgent order products, and rationally allocate materials to ensure the timeliness and accuracy of material supply in each process, so as to achieve the optimal allocation of production resources. Improve the overall efficiency of the production line and quickly respond to the changing needs of the market.

4 Digital Twins and Deep Learning Collaborate to Enable Adaptive Production Lines

4.1 Accurate Modeling: Integration of Multi-Source Data to Achieve Virtual Model Evolution

There are some errors in the initial model construction of digital twins, and deep learning optimizes the model with the help of the learning ability of mass production data. The actual operation data of the equipment and measured product data under different working conditions are input into the deep learning model, key features are extracted and fed back to the digital twin model layer, and model parameters are modified to make the simulation of the physical entity of the virtual production line more accurate. For example, in the machining production line, deep learning analyzes the tool wear process data and dynamically updates the wear state of the tool model in the digital twin to ensure that the virtual machining process is consistent with the actual process, providing a reliable basis for subsequent process optimization and quality prediction.

4.2 Real-Time Monitoring: Intelligent Perception of Abnormal Production Line Status

Digital twins map production line status in real time, and deep learning makes intelligent judgments on this basis. Through deep learning analysis of real-time data, it can quickly identify abnormal conditions of equipment such as abnormal vibration, temperature sudden change, and production beat disturbance, which can not only accurately locate the fault point, but also predict the scope and development trend of the fault. Once an anomaly is found, an alarm is immediately generated on the digital twin visual interface, and detailed fault diagnosis reports and response suggestions are pushed to the operation and maintenance personnel to realize the span from passive maintenance to active prevention, greatly reducing the downtime of the production line and ensuring the continuity of production.

4.3 Fault Prediction: Data-Driven Proactive Maintenance

Combining the historical data storage of digital twin and the prediction ability of deep learning, a fault prediction model is constructed. Deep learning deeply analyzes the time series data such as temperature, pressure, and energy consumption accumulated during long-term operation of the equipment, excavates the characteristic patterns of potential faults, and predicts the probability, time node, and possible fault types of the equipment in advance by combining the life cycle law of the equipment. Simulate the fault occurrence scenario in the digital twin environment, rehearse the effect of the maintenance plan, assist the operation and maintenance personnel to prepare spare parts in advance, arrange the maintenance period reasonably, reduce the maintenance cost, improve the availability of equipment, and extend the average trouble-free time of equipment.

4.4 Process Optimization: Dynamically Adjust Production Parameters to Improve Product Quality

Digital twins simulate the production process under different process parameters, and deep learning analyzes the correlation between process parameters and product quality data. In the injection molding production line, the deep learning model optimizes the process parameters in real time in the digital twin according to the influence law of the plastic raw material characteristics, mold temperature, injection molding pressure and other parameters on the product appearance, dimensional accuracy and mechanical properties, and combines with the feedback of real-time product quality detection, driving the physical production line to automatically adjust the injection molding process and continuously improve the product pass rate. Fast response to raw material, product specification changes, enhance flexible manufacturing capacity of the production line.

5 Challenges Faced and Coping Strategies

5.1 Data Quality and Security Issues

Production line data comes from a wide variety of sources and formats, and there are problems such as noise, missing, duplication, etc., which affect the training effect of deep learning model and the accuracy of digital twin model. At the same time, the production data involves the core technology and process secrets of the enterprise, and faces the risk of data leakage and tampering. It is necessary to establish a data preprocessing process and use data cleaning, de-noising, filling, standardization and other technologies to improve data quality. Strict data encryption, access control, and network security protection systems are deployed, and new technologies such as blockchain are adopted to ensure that data is trusted and traceable, and to ensure the security of data assets.

5.2 Model Fusion and Optimization Problems

Digital twin model focuses on physical process simulation, while deep learning model focuses on data intelligent processing. The integration of the two models faces challenges such as incompatible interfaces and inconsistent knowledge representation. With the increase of the complexity of the production line, the computational complexity of the model increases sharply, and the real-time performance is difficult to guarantee. It is necessary to develop a unified model integration framework, standardize data interaction interface and model fusion mechanism, promote interdisciplinary team collaboration, and overcome the technical difficulties of model fusion. By using the technology of model compression, distributed computing and edge computing, the calculation performance of the model is optimized, the running efficiency of the model is improved under the premise of ensuring the accuracy, and the real-time decision-making needs of the production line are met.

5.3 Talent Shortage Dilemma

The integrated application of digital twin and deep learning requires practitioners to have interdisciplinary knowledge, not only master manufacturing expertise such as mechanical engineering and automation, but also master data science and computer science skills. At present, the shortage of compound talents restricts the popularization of technology. Enterprises should strengthen internal personnel training, formulate interdisciplinary training plans, and encourage employees to participate in industry-university-research cooperation projects; Colleges and vocational colleges need to adjust professional Settings, set up integrated courses, train new talents to meet the needs of intelligent manufacturing, and inject a steady stream of intellectual support for industrial development.

6 Future Development Trend Outlook

6.1 Full Life Cycle Digital Twins Are Deeply Integrated with Deep Learning

In the future, the digital twin coverage of the whole life cycle from product design, process planning, manufacturing to after-sales service will be realized, and deep learning will be implemented throughout. In the product design stage, market demand analysis based on deep learning assists design innovation, and digital twins simulate product performance in advance; Continuous optimization in the production stage; In the after-sales stage, digital twins are used to remotely monitor the use status of products, deep learning is used to predict product maintenance needs, and product life is extended through remote upgrades and intelligent diagnosis services to maximize the value of the whole life cycle of products.

6.2 Multi-Production Line Collaboration and Cluster Intelligent Upgrade

For mass customization production needs, the collaboration between multi-production lines and multi-factories will become increasingly close. Digital twin builds a cross-regional and cross-enterprise production network model, deep learning optimizes collaborative scheduling and resource allocation strategies, realizes accurate coordination of raw materials, parts and finished product logistics distribution, dynamic balance of production line capacity, improves the overall competitiveness of industrial clusters, creates an intelligent manufacturing ecosystem, and promotes the manufacturing industry to take a big step forward in the direction of high-end, intelligent and collaborative.

6.3 A New Intelligent Production Model of Man-Machine Integration

With the further development of artificial intelligence technology, digital twins and deep learning help to achieve human-machine integration production scenarios. Operators use augmented reality (AR) and virtual reality (VR) technology to deeply interact with intelligent machines in the digital twin environment, deep learning models interpret human intentions in real time, intelligent machines accurately assist human operations, give full play to human creativity and the precision and efficiency of machines, reshape the production organization of future factories, and open a new era of intelligent manufacturing with human-machine harmonious coexistence.

7 Conclusion

The integration of digital twins and deep learning has brought transformative development for adaptive automated production lines and is a key force for manufacturing to move toward intelligence, efficiency and flexibility.

In terms of accurate modeling, the two work together to break traditional limitations. Deep learning analyzes massive production line data, drives the accurate evolution of digital twin models, lays a solid foundation for subsequent applications, and makes the digital management of production lines more accurate and dynamic. Real-time monitoring level to achieve a qualitative leap. Digital twins map production lines in real time, and deep learning endow them with intelligent perception, which can quickly identify anomalies, locate the root cause of faults, predict the development trend, turn passive maintenance into active prevention, reduce downtime, ensure production continuity, and cast a "protective shield" for enterprises. Fault prediction has the advantage of foresight. The data accumulated by the digital twin for a long time can help deep learning to mine fault characteristics, build accurate models combined with the parameters of the whole life cycle of the equipment, simulate and preview in the digital twin environment, assist operation and maintenance personnel to plan maintenance in advance, reduce costs, extend the time without fault of the equipment, and improve availability and economic benefits. Process optimization greatly enhances flexible manufacturing capabilities. Digital twin virtual model simulates the process, deep learning insights into data, drive optimization, such as real-time adjustment of parameters in the injection molding production line, adapt to changes in raw materials and product specifications, and improve the market resilience of enterprises.

Although the current stage faces challenges such as data, models, and talents, the problem will eventually be overcome with the maturity of relevant technologies and training systems. Looking forward to the future, the full life cycle integration will deepen the penetration of the two in the manufacturing industry, multi-production line collaboration and cluster intelligent upgrading will build an efficient ecology, and human-machine integration will open a new era of intelligent manufacturing. By seizing opportunities and responding to challenges, enterprises can stand out in the wave of transformation and upgrading, achieve sustainable and high-quality development, and help create a prosperous material civilization.

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