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Real-time Monitoring and Optimization of Industrial Robots Based on Digital Twin Technology

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Abstract. With the global optimization and reform of industrialization, the traditional manufacturing industry is accelerating its transformation toward intelligence and digitalization. Digital Twin (DT) offers a revolutionary solution for the full-life cycle management of industrial robots by establishing real-time mapping and bidirectional interaction between physical entities and their virtual replicas. Aiming at the limitations of traditional monitoring and optimization modes for industrial robots in response speed, early warning accuracy, collaboration efficiency and adaptability to complex scenarios, this paper systematically reviews the research and application progress of DT technology in the field of industrial robots. First, it combs the core technical system of DT-driven monitoring and optimization for industrial robots, including three modules: multi-dimensional modeling, real-time data interaction and scenario-customized algorithms. Second, it classifies and summarizes the research achievements and technical characteristics of multiple sub-directions according to three major application scenarios: fault prediction, remote monitoring and collaborative operation. Finally, it prospects the future development trends such as the deep integration of artificial intelligence (AI) and DT, cross-platform collaboration and lightweight deployment.

Keywords: digital twin, industrial robot, monitoring, optimization

1. Introduction

With the rapid development of AI, machine learning, digital modeling, big data, cloud computing and other technologies, Digital Twin (DT) has been rapidly developed and widely applied in the mechanical engineering and related fields. The operational reliability and stability of industrial robots are of crucial importance, as they directly affect production efficiency, product quality and corporate benefits. As an emerging digital technology, DT constructs a virtual model corresponding to physical entities to realize real-time system monitoring, data analysis and fault prediction.

In the global wave of automation and intelligence in the manufacturing industry, industrial robots have become indispensable core equipment, which are widely used in key fields such as automobile manufacturing, electronic assembly and precision machining. However, the traditional management mode of industrial robots is confronted with four core pain points:

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Monitoring mainly relies on manual inspection and offline data analysis, leading to delayed responses to abnormal states such as motor faults, thermal drift and assembly deviation. Consequently, losses caused by unplanned downtime account for 15% to 20% of the total production costs in the manufacturing industry.

Operation and maintenance decisions depend on empirical judgment, with the accuracy of fault early warning being less than 70%. In addition, the capabilities of remote monitoring and cross-regional collaborative optimization are inadequate.

Single-machine optimization and multi-machine collaboration lack a global perspective, making it difficult to adapt to the demands of personalized production and dynamic capacity adjustment.

Traditional algorithms are unable to meet the real-time optimization requirements under multi-physics field coupling and high-dynamic working conditions, resulting in insufficient technical adaptability.

Against this background, relying on the ternary architecture of physical entity - virtual replica - data link, DT technology realizes the visualization of operational status, intelligentization of fault prediction and dynamicization of process optimization, thus becoming the core technical approach to address the above pain points.

2. DT-driven monitoring and optimization system for industrial robots

The application of DT technology in the monitoring and optimization of industrial robots is based on a trinity core technical system of modeling-communication-algorithm. These three components support each other and form a closed-loop process of virtual-physical mapping - data transmission - intelligent decision-making.

2.1. Multi-dimensional accurate modeling technology

Modeling technology is the unshakable foundation of DT technology, which requires the realization of triple accurate mapping in the geometric, physical and behavioral dimensions.

• Geometric dimension: 3D models of robot parts (e.g., links and joints) are usually built using software like Computer-Aided Design (CAD) and Building Information Modeling (BIM), and these are described in detail in terms of their geometric parameters and spatial interactions. Laser trackers calibrate the coordinate system and laser scanning and other non-contact measuring techniques are used to obtain the geometric data of industrial robots.

• Physical dimension: The study theme is the nature of coupling between multi-physics fields, and the real physical properties and working conditions of objects. Many sensors collect various physical data (e.g., power, electromagnetism and fluid dynamics). The finite element technique and other numerical simulation methods build physical models and the measured sensor data corrects the physical parameters to be sure that the virtual model and the real physical properties of the object are consistent.

• Behavioral dimension: Delicate behaveioural data are recorded to determine operation patterns, deduce motion motivations and forecast future behaviours, which offers an understandable behavioural foundation to precise decision-making. The two dimensions, along with this one, are the pillars of the multi-dimensional modeling.

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2.2. Real-time data interaction technology

The most important bridge connecting DT technology is the real-time data interaction technology that will help achieve dynamic mapping between physical entities and virtual models. This technology is based on the premise of building a low-latency, high reliability and bidirectional synchronous data flow closed loop.The whole system gathers different physical data by using sensors and Internet of Things (IoT) terminals and achieves efficient data transmission based on network like 5G and Time-Sensitive Networking (TSN), and communication protocols like Message Queuing Telemetry Transport (MQTT) and Open Platform Communications Unified Architecture (OPC UA). Data cleaning, fusion and real-time analysis are then implemented by using edge computing and stream processing technologies. In addition, the incremental update and event-driven mechanism are applied to realize the millisecond-level synchronous response of the virtual model to the physical state, and support the reverse control of physical entities by simulation decision instructions from the virtual end. This technology effectively guarantees the dynamic fidelity and intelligent collaboration capability of DT, providing solid data support for applications such as predictive maintenance and optimal regulation.

2.3. Scenario-customized monitoring and optimization algorithms

Algorithms are the core of DT technology to realize intelligent decision-making, and corresponding customized schemes need to be designed for different application scenarios.

• Fault prediction algorithms: Long Short-Term Memory (LSTM) neural networks, Support Vector Machines (SVM) and other machine learning algorithms are used for fault prediction of motors and electromechanical systems. The unused useful life (RUL) of the components is estimated through the analysis of the operational data to accomplish preventive maintenance.

• Anomaly detection algorithms: The emphasis is on the multi-physics field coupling scenario, where multi-physical information hybrid convolutional autoencoders are used to achieve the accurate detection of small anomalies by collecting multi-dimensional feature information of operational data.

• Optimization algorithms: Optimization of operation processes (collaborative operation process optimization (genetic algorithm, reinforcement learning), operability and thermal control optimization (customized reinforcement learning), path planning optimization (Astro algorithm, dynamic programming).

• State monitoring algorithms: In the case of collaborative robots, a hybrid DT scheme is used to trade off between monitoring accuracy and real-time performance.

3. Research progress of key application scenarios

3.1. Fault prediction scenarios

Fault prediction is one of the core application scenarios of DT technology. Potential faults can be detected in advance and early warnings can be sent to users by real-time monitoring and analyzing physical operation data. For example, in the field of medical applications, stroke is the second leading cause of death worldwide. Traditional monitoring and nursing schemes have significant drawbacks and are unable to respond to complex physiological changes in a very short time. The emergence of DT technology provides a new solution: it collects physiological data from patients through a variety of sensors, conducts real-time monitoring and data analysis, and predicts patients'

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health status and medication effects [1]. In the field of industrial steam systems, DT and data-driven prediction can greatly reduce energy waste, realize a more intelligent control process and improve the efficiency of thermal engine systems [2]. In the field of tool condition monitoring, traditional detection methods are extremely inefficient and cannot meet the needs of modern manufacturing. The combination of DT and machine learning algorithms can well address these pain points [3]. At the same time, in many other fields such as power supply system inspection and urban rail transit inspection, DT models can also be constructed for real-time monitoring and fault prediction.

3.2. Remote monitoring and virtual-physical interaction scenarios

The main purpose of remote monitoring and virtual-physical interaction scenarios is to break through spatial limitations, realize remote status management and operation guidance of industrial robots, and ultimately achieve automation and intelligence of production processes. For example, in nuclear reactors, traditional detection methods are mostly inclined to static detection, lacking dynamic detection and data-driven capabilities. The combination of DT technology and large language models (LLM) can realize real-time data monitoring, analysis and optimization, as well as powerful human-computer interaction capabilities [4]. Similarly, in the field of industrial robots, the same method can be used to construct corresponding DT models, monitor key operational data and realize remote control, thus replacing humans to work in complex and dangerous working environments.

3.3. Collaboration and operation optimization scenarios

The main purpose of collaboration and operation optimization scenarios is to improve the collaboration efficiency of multi-robot systems and the operational performance of single robots, and propose optimization solutions for various industrial application scenarios. For example, in the life optimization of fuel cells, traditional methods have great limitations, while the emerging data-driven model combining physical neural networks and DT technology shows great potential. Its advantage lies in the integration of physical and digital driving methods: it realizes higher-precision prediction and optimization by summarizing and analyzing historical data and physical laws, thus extending the service life of fuel cells [5]. In terms of warehouse logistics management, the entire logistics industry is actively carrying out digital transformation, and DT technology is one of the key technological drivers. Through high-precision modeling and mapping of physical logistics systems, it realizes real-time digital simulation, monitoring and optimization. It can help users predict potential operational problems and improve production efficiency through data analysis combined with AI and IoT technologies [6]. At the same time, in urban construction and energy management, DT technology, combined with IoT and blockchain technologies, ensures operational feasibility, data synchronization security and energy flow optimization, so as to achieve sustainable development in urban construction [7].

4. Typical practical cases

4.1. Typical domestic cases in China

Relying on the high-precision 3D model of the whole plant and the industrial internet platform, this nuclear power plant adopts an independently controllable 3D engine and integrates a variety of complex operational data. Through data sharing, it realizes the application of all-round business

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scenarios such as intelligent monitoring, digital and intelligent operation, and smart maintenance. It achieves comprehensive perception of the nuclear power plant, greatly improves the reliability and operation efficiency of equipment, thereby further ensuring the safe production and sustainable development of the nuclear power plant.

China Southern Power Grid Corporation is accelerating the construction of a digital twin power grid. Through the application of DT technology, it has realized all-round intelligent monitoring of engineering projects, effectively ensuring that the progress of project construction is controllable and manageable. At the same time, the company has built a digital twin of the power grid covering 100,000 nodes, which can support the closed-loop interaction of dispatch control and electromagnetic transient simulation, effectively improving the capacity of new energy consumption and the level of fault early warning.

Tencent Taopu Smart Innovation City Industrial Park has realized AI-based intelligent optimization control and management linkage of the energy system with the support of DT technology, which promotes data sharing and breaks data silos. This technology has also been applied to the intelligent and refined management of building energy and building environment, effectively solving the problems of high energy consumption and low energy efficiency in park operation.

4.2. Typical international cases

BMW Group has created DT models of all its global factories, and built a virtual factory of BMW Group based on NVIDIA Omniverse in the industrial 3D metaverse application. The virtual factory can simulate the real-time execution of design, robot and logistics systems, thus realizing virtual collision inspection. This inspection is digital and automated: by using operational data combined with 3D scanning technology, the movement and rotation of vehicles on the production line are simulated with high precision, and the system can automatically check potential collision risks. What previously required nearly four weeks of physical testing can now be completed through DT technology in just three days.

Siemens AG has developed a variety of DT modeling software, which can provide customers with flexible digital simulation solutions. Through the combination of virtual and physical, it provides users with an efficient and accurate simulation test platform, which is widely used in teaching, scientific research, industrial manufacturing and other fields.

By adopting the NVIDIA Omniverse platform technology, Foxconn has built a DT platform for operating smart factories, and realized intelligent data analysis and decision output in the real world through the integration of virtual and physical. The platform can realize the virtual assembly of the entire production line, and quickly migrate and copy production line layouts among factories around the world, greatly accelerating the construction speed of smart factories. In addition, its DT platform can also simulate and optimize complex robot tasks to achieve collision-free motion planning.

5. Future development trends

5.1. Deep integration of AI and digital twin

AI technology is closely integrated with DT technology, and their combination can realize the upgrade from data-driven to intelligent decision-making. For example, the DT modeling method based on generative AI can automatically generate high-precision virtual models of robots, thus greatly shortening the modeling cycle; reinforcement learning algorithms will realize autonomous

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optimization and adaptive adjustment of industrial robots without human intervention. In addition, LLMs will be applied to the human-computer interaction of DT systems, supporting the issuance of natural language instructions and intelligent fault diagnosis consulting. In the future, functions such as equipment inspection and process optimization can be realized by AI agents equipped with DT systems. The DT system conducts real-time data monitoring and process optimization, while the AI agent is responsible for the perception, analysis and strategy formulation of complex working conditions. The combination of the two can better respond to sudden and actual production situations [8]. On the other hand, in the energy field, the traditional biogas production mode mostly focuses on short-term prediction and monitoring, while the new architecture combining AI and DT technology can provide more reliable real-time monitoring, long-term prediction and process optimization [9].

5.2. Cross-platform collaboration and large-scale application

In the future, DT systems will not be used on isolated industrial robots, but it will break the boundaries of one robot and one production line to achieve collaborative optimization across companies and industries. As an illustration, real-time traffic models could be developed through the aggregation of diverse traffic data, which may include traffic flow and vehicle parameters, in addition to important situational factors, such as weather conditions, road conditions and passenger behaviour, using DT technology. By real-time correspondence with the real-life traffic scenario, precise modeling and mapping is achieved and predictive analysis is performed to enhance efficiency of managing urban traffic [10]. Simultaneously, the spread of DT technology will occur not only to high-end manufacturing sectors (e.g. automobiles and electronics) to the general manufacturing industry but will also increase the range of applications and reduce the technical barrier to access. This will facilitate large scale use of DT technology in manufacturing industry and the digital and intelligent transformation of the traditional manufacturing industry.

6. Conclusion

Digital twin has become one of the fundamental technologies of intelligent manufacturing, the technical properties of which successfully overcome the long-standing gaps and shortcomings of traditional methods of monitoring industrial robots, as well as the shortcomings of optimization systems. This paper has a systematized review of the trinity technical architecture of multi-dimensional high-precision modeling, low-latency real-time data interaction, and scenario-oriented intelligent algorithms that facilitate the closed-loop functioning of virtual-physical mapping, data fusion, and autonomous decision-making. Research has confirmed that digital twin technology has produced impressive application outcomes in fault prediction, remote monitoring, and joint operation. Its applications have not only significantly enhanced the precision of fault early warning, but also operational performance and multi-robot coordination performance. In the meantime, practical value of it in preventing unplanned downtime, reducing operation and maintenance costs, and enhancing equipment reliability has been further confirmed by the relevant cases in China and abroad. The primary input of this paper is the systemic and organized review of digital twins in the sphere of industrial robots, defining technical directions, category of scenarios, and engineering standards, which may give a clear guideline to the corresponding researchers and industrial professionals. However, the limitations of this review also exist: that is primarily dealing with mature applications and does not discuss in detail lightweight modeling, crossplatform data security and high degrees of fidelity in mapping in extreme working conditions. In addition, the integration

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of digital twin with large language models and autonomous artificial intelligence remains at the conceptual stage with insufficient experimental verification, requiring further research, development and application. From the perspective of current research, future efforts should continue to promote the accuracy and realtime performance of digital twin modeling, strive to realize the deep integration of artificial intelligence and digital twin, develop lightweight models suitable for edge deployment, ensure crossplatform interoperability and data security, and highlight prominent engineering practicality. Through the above research, it will not only facilitate the largescale popularization of digital twin in general manufacturing, but also enable the fulllifecycle intelligent management of industrial robots.

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