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A Multi-level Heterogeneous Model data Framework for Intelligent Factory Digital-Twin Systems

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Abstract

By using physical models and continuously updated sensor data, digital-twin can map industrial physical space entities to cyber space model system to realize the whole life cycle simulation and evaluation of complex industrial entities, which is an important key technology to promote industry 4.0. The management of complex heterogeneous models of digital-twin systems in an intelligent factory is facing severe challenges. This paper presents a multi-level heterogeneous model data framework for intelligent factory digital-twin systems. The multi-level integration framework is established for all levels of unit equipment, production lines, workshops and factories, as well as cross-domain product design, manufacturing, operation and maintenance. The paper presents an industrial model data management framework for multi-level digital-twin systems, and designs an data interoperability mechanism for cross-domain heterogeneous models based on knowledge ontology semantic networks. The proposed framework can provide an important theoretical framework for the management of complex model systems of digital-twin systems in intelligent factory.

Keywords: Model engineering, digital-twin, intelligent factory, industrial big data, industry Internet of things

1. Introduction

Since Grieves of the University of Michigan first proposed the concept of digital twin in article (Grieves and Michael, 2005), digital twin has gradually expanded to analog simulation, virtual assembly and 3D printing. Nowadays, the concept of digital twin, which is widely accepted in the industry, refers to the digital model of physical objects in the real world. The model can evolve in real time by receiving data from physical objects, thus keeping consistent with the physical objects in the whole life cycle. Digital twin technology maps physical equipment into virtual space by means of digitization, forms a digital image that can be disassembled, copied, transferred, modified, deleted and repeated, which deepen the understanding of physical entities by operators, and can stimulate people to explore new ways to optimize design, manufacturing and service.

With the development of digital transformation of enterprises around the world, digital twin has become a solution for manufacturing enterprises to move towards industry 4.0, which has played a great role in promoting the process of global industry 4.0. With the help of cloud manufacturing (Ren et al., 2017), Internet of things and big data technology, digital twin collects limited direct data of physical sensor indicators, and with the help of large sample library, it can infer some indicators that could not be directly measured by machine learning. In addition, digital twin can combine the data acquisition of Internet of things, the processing of big data and the modeling and analysis of artificial intelligence to realize the evaluation of current state, diagnosis of past problems, and prediction of future trends (Ren et al., 2021). The results of analysis can simulate various possibilities and provide more comprehensive decision support.

Intelligent factory realizes the intelligent production process (Ren et al., 2020) by building intelligent production system and network distributed production facilities. The digital twin system can model the whole factor of product production process, and then make virtual mapping to the whole intelligent factory. The purpose of modeling is to simplify and model the knowledge that we have formed in understanding the physical world or problem. The purpose or essence of digital twin is to eliminate the uncertainty of various physical entities, especially complex systems, by digitizing and modeling, exchanging energy with information. Therefore, the establishment and scientific management of the digital model of physical entities is the source and core technology of creating digital twins and realizing digital twins, and also the core of the "digital" phase. The model management in virtual space is one of the important problems.

At present, the challenges faced by the intelligent factory digital twin system in the process of managing virtual models mainly include the following two aspects. First, the models in the digital twin virtual space correspond to different granularity models in multiple levels in the physical space. How to realize the integrated modeling of equipment, production line, workshop and factory at all levels, multi-level and multi granularity, It is a difficult problem to face. Secondly, there are many kinds of entities in intelligent factory, and the model has the characteristics of multi-source and cross domain heterogeneity. How to establish association and realize interoperability among heterogeneous models is also a difficult problem.

Based on the above two problems, this paper proposes a multi-level heterogeneous model data framework for intelligent factory digital twin systems, aiming at solving the problems faced by intelligent factory digital twin system in virtual model management.

2. Related work

2.1. Digital-twin

Digital twin, as an information technology which uses model, data, intelligence and integrates multi-disciplinary, has attracted widespread attention in the industrial field in recent years. In 2011, AFRL proposed the concept of digital twin of fuselage to solve the maintenance problem of fighter body. Based on digital twin, GE company of the United States adopts advanced technologies such as big data and Internet of things to realize real-time monitoring, fault diagnosis and health prediction of engines (Grieves, 2011; Grieves and Vickers, 2017). Based on the idea of digital twin, Siemens builds a system model of production process flow, analyzes all links of production process through simulation, and realizes the virtualization and digitization of product design and manufacturing process. With the development of digital related technologies, NASA proposed in 2010 to apply digital twin technology to the design and optimization of future spacecraft, companion monitoring and fault assessment (Shafto et al., 2010). In 2011, the Air Force Research Laboratory proposed to use digital contracture to realize the functions of state monitoring, life prediction and health management in future aircraft (Tuegel et al., 2011). With the help of digital twin and traditional fault analysis method, U.S.General Motors(Li et al., 2017) analyzes the fatigue crack and other faults of aircraft and achieves more accurate prediction.(Wang et al., 2011)proposed a digital twin based spacecraft system engineering, and studied the spacecraft system engineering model, application framework and technical framework.

2.2. Model engineering

(Zhang et al., 2011; Zeigler and Lin, 2015; Zhang et al., 2013) proposed the concept of model engineering in 2011, and provided the knowledge system of model engineering. It aims to improve the credibility of the whole life cycle of the model and reduce the cost of model development and management by providing the theory, technology, methods, standards and tools supporting the standardized, systematic and quantifiable engineering management and control of the model life cycle process. (Zhang et al., 2020) introduces the concept of model maturity, and proposes an index system to evaluate the maturity of the model and a method for model maturity evaluation.

2.3. Digital twin in intelligent factory

Intelligent factory is an important carrier to realize intelligent manufacturing, mainly through the construction of intelligent production system, network distributed production facilities, to realize the intelligent production process. The industrial production process is a very complex system engineering. Digital twin technology can connect the physical devices in the physical world with the virtual devices in the information world, so that the virtual devices in the intelligent factory can reflect the production situation of the physical devices in real time and control the actual production process. Based on the direction of digital twin technology and intelligent factory, (Tao et al., 2017) proposed the implementation mode of digital twin workshop, elaborated the system composition, operation mechanism, characteristics and key technologies of digital twin workshop, designed the reference system architecture of digital twin workshop, and studied and analyzed the key problems of realizing the information physical integration of digital twin workshop, It provides a reference for enterprises to practice digital twin workshop. (Zhao et al., 2019) proposed a 3D visualization real-time monitoring method for digital twin workshop, studied the data-driven virtual workshop operation mode based on workshop operation logic modeling, realized the dynamic monitoring of the whole process and all elements of the workshop, designed and developed a prototype system, and verified it by an example. (Knapp GL et al., 2017) established a digital twin model for additive manufacturing process to predict the temperature field and velocity field, cooling rate, solidification parameters and sediment geometry, so as to reduce the number of experiments for adjusting process variables. The experimental results show that the model can accurately predict the temporal and spatial changes of metallurgical parameters that affect the structure and properties of parts.

(Coronado PDU et al., 2018) proposed a data acquisition method for equipment based on MES and MTConnect protocol, and applied it to production control and optimization. MES is based on Android mobile device application development and implementation, using WEB services to provide cloud access, data backup and computing functions. At the same time, MES is integrated with the data generated by MTConnect standard CNC machine tools, so as to realize a complete digital twin model of workshop. (Ge et al., 2017) proposed a symbiotic simulation framework based on the concept of digital twin, aiming at the prominent problem of stable model parameters without self evolution ability in the prediction of remaining service life of equipment, The Wiener state space model is used as the basic simulation model in the framework. multi-level heterogeneous model engineering framework.

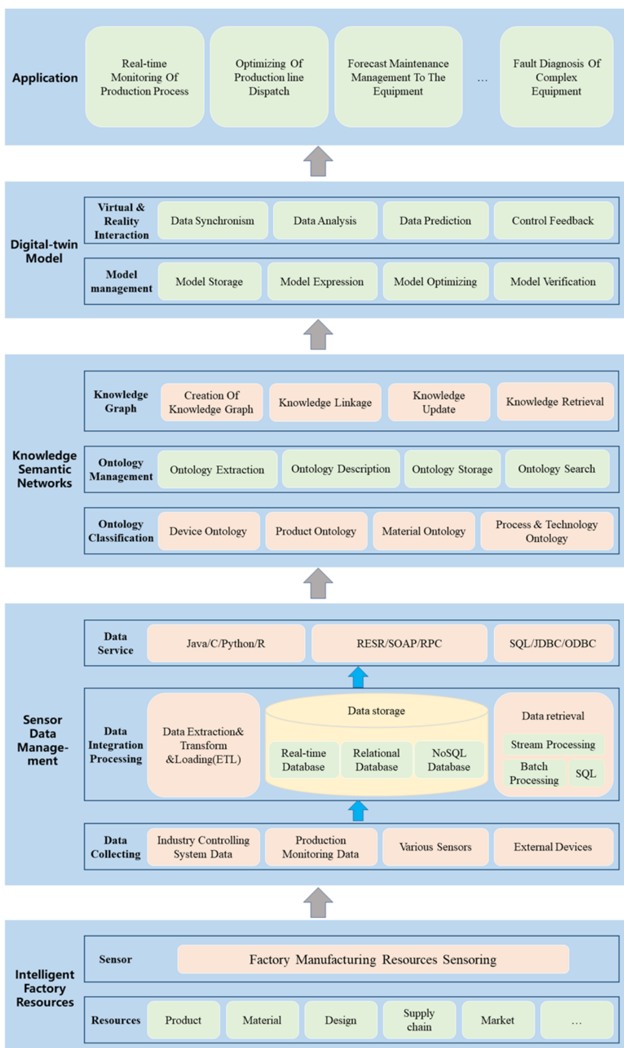

Figure 1. Multi-level heterogeneous model data framework for intelligent factory digital-twin systems.

3. Multi-level heterogeneous model engineering framework

3.1. Knowledge semantic networks layer

Digital twin needs to express all data and information in physical space, form a unified data carrier, and realize data mining analysis and decision-making. These data involve spatial model, Internet information, real-time perception of Internet of things, professional knowledge, audio, video, text and so on, so the data of intelligent factory is heterogeneous and diverse, and the knowledge is also diverse.

The knowledge resources in digital twin system can be directly extracted from entity resources, including static process mechanism knowledge, equipment digital model, etc. the other part can be obtained indirectly through data processing and information mining analysis, including product quality evaluation models, residual life prediction models (Ren et al., 2020; Ren et al., 2021; Ren et al., 2017), fault diagnosis models, complex process identification models, etc. Therefore, in the knowledge semantic network layer, it is necessary to describe the diversified knowledge through ontology, and finally form the knowledge map. In the process of ontology construction, domain experts are required to participate. The domain experts here may come from different positions according to the types of ontology, including system R & D personnel, front-line operators, operation and maintenance personnel, equipment management personnel, etc.

For the ontology of the whole digital twin system, we classify it into the equipment ontology library, product ontology library, material ontology, process ontology library and other categories of ontology libraries according to its category, in order to better manage and operate the ontology in the future. The ontology management layer is above the knowledge map layer. In this layer, we use the specific knowledge extracted from the data to extract, describe and store the ontology, and give it the function of retrieval, so as to provide support for the unified retrieval of knowledge. The description of ontology is very important, including the description of the category of ontology, the corresponding ontology and the specific steps of the design process (such as requirement analysis, material selection, etc.)

It includes four aspects: A. category: describe the category corresponding to ontology; B. Stage: describe the specific steps of the design process corresponding to ontology, such as requirement analysis, material selection, etc.; C. Core parameters: specifically indicate which core parameters are involved in the corresponding description ontology; D. Knowledge type: refers to the specific type of knowledge. In addition, according to the characteristics of different knowledge, the content of description ontology can be expanded to better summarize specific knowledge and provide better support for knowledge retrieval.

In the process of ontology construction, we can use a semi-automatic method, that is, template-based ontology generation method. The description ontology can be obtained through the interaction of visual interface. Domain experts only need to consider the accurate and complete expression of description ontology, and do not need to consider the recognition and storage of knowledge from the perspective of computer. The main steps of ontology-based knowledge template acquisition method include the following four parts: a; B. Concept stage; C. Formalization stage; D. Implementation stage; E. Test phase.

After summarizing the knowledge in the system, we need to form a knowledge map for the whole digital twin system. Knowledge mapping can not only measure and visualize the relationship between all the knowledge in the system, but also help to update and retrieve the knowledge, so as to realize the management of the whole life cycle of knowledge.

3.2. Digital-twin model layer

Through the construction of knowledge map, the system forms the understanding of the data information in the whole intelligent factory. Next, we need to use the knowledge to digitize the physical world of the whole intelligent factory. This process needs to bridge physical objects with knowledge, so as to express them as digital models that can be recognized by computers and networks. The system uses digital twin modeling language and some general modeling tools to form conceptual model and information model. The conceptual model describes the architecture of digital twin system from a macro perspective. The information model base includes object model base with personnel, equipment and facilities, materials, site environment and other information as the main content, and production information rule model base Product information rule model base and technical knowledge rule model base are the main content of rule model base.

For many virtual models in digital twin system, a scientific management system is needed to manage the whole system model. The content of model management mainly includes model expression, model storage, model classification and model optimization. The expression of model refers to the use of digital twin modeling language or general modeling tools to model the system, and the resulting model needs to be stored in the specified location of the system according to category, function, etc. The ideal digital twin model involves geometric model, physical model, behavior model, rule model and other multi-dimensional, multi-temporal and multi-scale models. It has the characteristics of high fidelity, high reliability and high precision, which enables the digital twin system to truly depict the physical world. Because the digital twin system is the digital expression of the physical world of the intelligent factory, another difference between the digital twin model and the traditional model is that it is a dynamic system, which can update and evolve the model in real time according to the changes of the physical world, so as to realize the dynamic real mapping of the physical world.

In addition, the digital twin model also emphasizes the interaction between the virtual and the real. The digital twin system can effectively analyze and utilize the data in the intelligent factory through the multi-source, multi type, multi structure, whole factor / whole process / whole business massive data synchronization of virtual and real world physical perception data, model generation data, virtual real fusion data and other high-speed production, so as to provide simulation, data prediction, data processing and data processing for the system and users Control feedback, etc.

3.3. Application layer

The application of digital twin system plays an important role in the whole life cycle of intelligent factory products. For product designers, under the traditional R & D design mode, paper and 3D CAD are the main product design tools. The virtual model established by them is static, and the changes of physical objects cannot be reflected in the model in real time, nor can they communicate with the product life cycle data such as raw materials, sales, market and supply chain. In the process of technical verification of new products, it is necessary to produce the products and carry out repeated physical experiments to obtain limited data. Digital twin breaks through the limitation of physical conditions, helps users understand the actual performance of products, and iterates products and technologies with less cost and faster speed. Digital twin technology not only supports three-dimensional modeling, realizes paperless parts design and assembly design, but also replaces the traditional research and development method of obtaining experimental data through physical experiments, and conducts virtual experiments by means of calculation, simulation, analysis or simulation, so as to guide, simplify, reduce or even cancel physical experiments. Users use simulation software such as structure, thermal, electromagnetic, fluid and control to simulate the operation of the product, test, verify and optimize the product. Digital twin not only shortens the product design cycle, improves the feasibility and success rate of product development, reduces the risk, and greatly reduces the cost of trial production and testing

Digital twin technology can be applied to different levels of manufacturing process, from equipment level, production line level to workshop level, factory level, etc. it runs through all links of manufacturing design, process management and optimization, resource allocation, parameter adjustment, quality management and traceability, energy efficiency management, production scheduling, etc., and simulates, evaluates and optimizes the production process (Ren et al., 2020), so as to systematically plan the production process, equipment and resources. At the same time, the digital twin technology can be used to monitor the production conditions in real time, find and deal with all kinds of abnormalities and instability in the production process in time, so as to achieve the goal of cost reduction, efficiency, quality and meet the requirements of environmental protection. In discrete industries, the application of digital twin in process planning focuses on the collaboration between manufacturing and design; in the process industry, mechanism or data-driven modeling of process is required by digital twin technology.

Under the traditional equipment operation and maintenance mode, when the equipment fails, it needs to go through a series of processes, such as finding the fault, calling the after-sales service personnel, and after-sales on-site maintenance. Customers' ignorance of equipment knowledge and communication barriers with equipment manufacturers often lead to failure that cannot be solved in time. The digital twin provides real-time virtual mapping of physical entities. The sensor inputs the data of temperature, vibration, collision and load into the digital twin model in real time, and inputs the data of equipment use environment into the model, so that the environment model of the digital twin is consistent with the changes of the actual equipment working environment, In- order to replace the worn parts in the scheduled downtime and avoid unexpected downtime. Through the digital twin, the fault diagnosis of complex equipment can be realized, such as the fault diagnosis of fan gearbox, power generation turbine, engine and some large structural equipment, such as ship maintenance.

4. Conclusions

In order to deal with the problem of virtual model management in the digital twin system of intelligent factory, a multi-level heterogeneous model data framework is proposed in this paper. The whole framework is based on the diversified data sources, data structures and data characteristics of intelligent factory, combined with diversified data analysis methods, the knowledge contained in ontology is extracted, and form the knowledge map of the whole intelligent factory. Then the digital twin model of intelligent factory is constructed by using knowledge, and the interaction between virtual and reality is realized through scientific model management method.

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