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Overview of Digital Twins in Mining Equipment

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Abstract: Digital twin technology is a real-time simulation skill based on computer models and real physical systems. Digital twin for extractive equipment combines physical equipment with virtual models to achieve comprehensive monitoring, prediction and optimization of extractive equipment and its operational status through data integration, simulation and analysis. The key elements of extractive equipment digital twin include sensor and data acquisition, physical model building, model calibration and validation, data analysis and decision support. By collecting the sensor data of the equipment, Efficacy of virtual environments in developing collaboration strategies between industrial robots and humans including parameters such as temperature, vibration, pressure, etc., and then the corresponding digital twin models can be established. These models can be calibrated and verified based on actual data to ensure their accuracy and reliability. Applications of digital twins for extractive equipment include operational status monitoring and prediction, optimization of operation and maintenance strategies, training and knowledge management. Digital twins can also record equipment operation data and fault information to form a knowledge base for subsequent fault diagnosis and decision-making. The application of digital twin technology for mining equipment can improve the efficiency and reliability of mining equipment, reduce operating costs, and help improve the technical level and training of employees.

Keywords: Digital twin technology; Mining equipment digital twin; Real time monitoring; Mining industry.

1. Introduction

In mine production, the operation and maintenance of mining equipment has always been the focus of attention. As one of the core elements of mine production, its stable operation and efficient maintenance are crucial to the smooth running of production. There are many challenges in the work of traditional extractive equipment, such as equipment failures that are difficult to find in time and lack of scientific basis for maintenance strategies [1]. These problems lead to high costs and low production efficiency, which seriously restrict the rapid development of mines [2].

Digital twin technology, as an intelligent integrated multidisciplinary simulation technology [3] and a representative of the new generation of information technology, has become the focus of international attention. It has been widely used in mining, aerospace, human-computer interaction, advanced manufacturing and other fields [4-9]. This provides a new method and means for monitoring, prediction and optimization of mining

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equipment. Digital twin can achieve comprehensive monitoring, prediction and optimization of equipment. By simulating the operating status and maintenance strategy of mining equipment in a virtual environment to predict the risk of equipment failure and optimize the operation strategy in advance, thus reducing the failure rate, improving the production efficiency and reducing the operation and maintenance cost. It introduces its basic concepts and principles, discusses the application scenarios of digital twins for extractive equipment, and provides an outlook on the current challenges and future development of digital twin technology for extractive equipment.

2. Digital twin basic concept connotation

2.1. Digital twin overview

Digital twin technology is an emerging field that integrates the application of computer simulation, virtual reality, Internet of Things and artificial intelligence. It achieves simulation, monitoring and optimization of equipment or processes by constructing a digital model of the real world and interacting with the actual physical system. in 2003, Professor Michael Grieves first proposed the concept of digital twin, defining digital twin as a digital representation of the integration between reality and virtual [10]. He applied digital twin to product lifecycle management and manufacturing process optimization and pointed out that digital twin can provide better decision support, collaborative work and innovation, thus the prototype of digital twin technology was born. In 2012 D S Stargel defined digital twin technology as multi-physics, multi-scale probabilistic simulation technology implemented in system integration [11]. The concept was first used in manufacturing by NASA's Apollo program [12-13]. It is now generally accepted that a true digital twin (Figure 1) enables automatic two-way data interaction between physical and virtual entities [14].

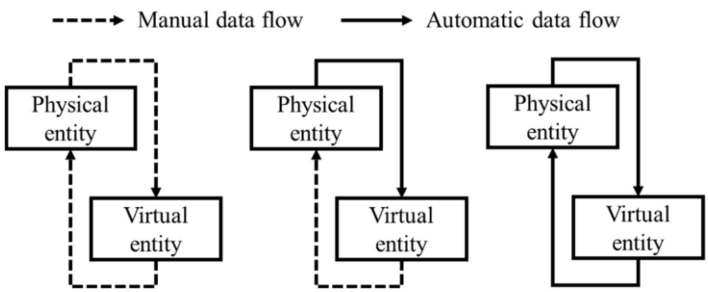

Figure 1. Schematic diagram of the digital twin process

2.2. Digital twin modeling

Modeling of a digital twin is one of the key steps in creating a digital twin, which involves establishing associations between physical and virtual entities and creating mathematical, physical, or computer models that can be used for simulation and prediction. It puts more emphasis on real-time interactive feedback with physical entities [15] and the ability to simulate and predict the full life cycle of a system. This needs to have the following capabilities:

- Accurately simulate the behavior and performance of the physical system and perform predictions and analysis based on current state and input data. It can simulate and predict systems by modeling their physical, chemical, biological, or other aspects.
- Acquisition and integration of data from different sources, including sensor data, monitoring data, historical data, and so on. These data will be used for parameter calibration, state update and performance evaluation of the model, etc.
- Acquire real-time data in real time and analyze and process the data in real time for timely decision making and optimization.
- Display the simulation results and prediction results of the system in a visualized form so that users can intuitively understand the state and performance of the system. At the same time, the user should be able to interact with the model to optimize and improve the system by adjusting parameters, inputs and strategies.

Digital twin modeling approaches can usually be classified into two types: data-driven and model-based digital twins [16]. Data-driven digital twins can be better adapted to the complexity and uncertainty of real systems [17], but may be challenging for systems that lack sufficient data or are difficult to collect. Model-based digital twins can utilize known physical laws and model knowledge [18], but require precise physical parameters and constraints when building the model, and need to verify the consistency of the model with the actual system. The two approaches are often combined in practical applications to better realize the modeling and application of digital twins.

Referring to the simulation life cycle process [19], a framework can be used as shown in Figure 2 [20]. In order to design the model, it is necessary to define the objectives and application scenarios of the model and understand the required inputs and outputs. Identify and define the variables and parameters to be tracked and simulated in the model. Create a conceptual model and define its architecture, the flow of interactions among them. Select the appropriate simulation software or programming language based on the needs and technical requirement. software such as Arena, Simio, etc. provide visual modeling and simulation capabilities, while programming languages such as C, C ++, Java, or Python provide a higher degree of flexibility and customization.

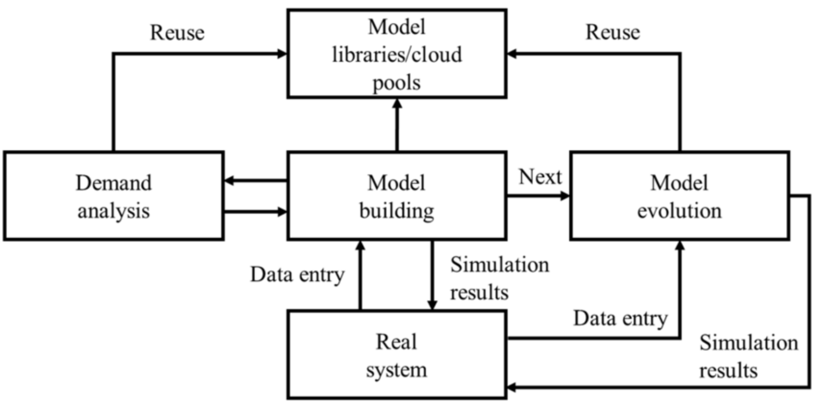

Figure 2. Digital twin construction framework

3. Digital twins empower mining equipment

3.1. Digital twins empowering the conveyor belt

Extraction equipment plays a important role in the mining and mining industry. Digital twin technology brings new opportunities for the development and optimization of extractive equipment. With the rapid development and increasing maturity of digital twin technology, digital twin technology in the field of extractive equipment is also developing day by day. Belt conveyor is one of the important equipment in mining [21]. Literature [22] investigates the digital twin-driven operation optimization method of long-distance belt conveyor, and establishes the virtual model of belt conveyor. Sensors and data acquisition systems are connected to the belt conveyor, and key parameters are collected in real time to monitor and analyze the operation status of the equipment in real time. Fault prediction and maintenance planning are performed. And validation is carried out. Literature [23] studied the scraper conveyor based on Kalman filtering and conducted experiments and simulation analysis (Figure 3).

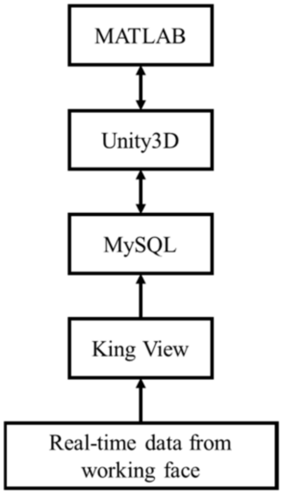

Figure 3. Scraper conveyor digital twin establishment process

3.2. Digital twins empower robotic arms

Robotic arm can replace human to work in bad environment and improve productivity [24]. Literature [25] studied the digital twin-based robotic arm disordered gripping structure and carried out virtual simulation layer design, control layer design, solid physical layer design and actual scene verification, and designed a robotic arm disordered gripping system that integrates 3D vision and digital twin technology. Literature [26] investigates the digital twin-based assembly modeling and simulation of construction robotic arms, which improves the reliability, safety, and efficiency of construction machinery and equipment, and reduces maintenance costs and failure risks. It helps engineering project management and operation teams to better monitor and manage mechanical equipment, optimize workflow, and improve construction quality and project efficiency.

3.3. Digital twin empowers road headers

Road headers can improve mining efficiency and enhance safety, but the current mainstream underground roadway excavation using a combination of cantilevered road headers and mono block drilling rigs has been difficult to meet the needs of excavation [27]. Literature [28] completes the coal mine intelligent road heading robot digital twin system and successfully applies it, which is capable of state sensing and data transmission, and improves the efficiency of road heading. Literature [29] researched the digital twin-driven cantilever road header virtual teaching memory cutting method through the teaching trajectory tracking based on iterative learning and fuzzy control. A new model of virtual teaching is proposed.

4. Digital twin key technology for mining equipment

4.1. Digital twin key technology analysis

Digital twinning of extractive equipment requires the creation of realistic 3D equipment models. The structure and parameters of the extractive equipment are modeled using computer-aided design techniques and 3D modeling software [30]. The geometry of the equipment is first modeled, and then the physical properties and performance parameters of the equipment are bound to the geometric model. Then the kinematic model of the equipment is established to describe the motion relationship, position and attitude changes of each component of the equipment. Literature [31] uses the surface topography model simulation method of fractal theory, the surface topography model fusion method of point cloud transformation, and the surface topography model reconstruction method of data to make the digital twin model more consistent with the physical entity. The digital twin modeling method proposed in literature [32] can be applied under multi-scale and multi-dimensional space. A multi-domain unified modeling proposed in literature [33] addresses the mapping theory of digital and physical space. Literature [26] effectively identifies assembly process bottlenecks and problems by modeling the robotic arm to improve assembly quality and efficiency.

In the mining digital twin, this needs to combine multiple sources of heterogeneous data, including real-time and historical data. Digital twin models utilize multi-source heterogeneous data to create an accurate description of the actual mining system. It can be updated and calibrated in real time to more accurately model and predict the behavior of the mine system. The control system can adjust the operating parameters of the actual equipment according to the prediction results and optimization suggestions provided by the digital twin model to achieve precise control and optimization [34]. By receiving real-time and historical data for updating and iteration, while the control system makes real-time decisions and controls based on the results of the digital twin model [35]. Through real-time monitoring and simulation prediction, the digital twin model can reflect the current state of the mining system and feedback the equipment operation status information and working condition environment information, etc. to the control system [36] to support real-time decision-making and adjustment. Using the inherent relative positional relationship between them, and taking the state data of the three machines as the feedback quantity, intelligent control of mining can be realized, and collaborative control of coal mining process can be realized [37].

Mining digital twin fault detection is the use of digital twin technology to monitor and detect faults and anomalies in mining equipment or systems. The digital twin model is an accurate simulation of a real mining system and can interact with real-time data from the actual equipment or system. Once an anomaly is detected, the digital twin model can diagnose and predict the fault based on historical data and equipment parameters. Possible causes of the failure and corresponding solutions are provided. And perform optimization and decision support to improve the performance and reliability of the equipment, literature [38] proposes MEFHP autonomous accurate service based on MEFHP autonomous learning, self-optimization mechanism and virtual verification.

Mining digital twin human-computer interaction can acquire data from on-site sensors and monitoring equipment in real time and feed it back into the digital twin model. This allows the operator to view the operating status of the equipment, parameter changes and other information in real time, to grasp the dynamics of the system in a timely manner, and make corresponding adjustments and decisions. The remote way to realize the manipulation and monitoring of the equipment and the on-site equipment for real-time interactive collaboration, to provide real-time support and decision-making. It is necessary to study the accurate reconstruction and mapping of 3D images based on digital twins and AI, the derivation and construction of intelligent twin digital bodies, holographic projection technology hybrid based on the precise characterization of multi-dimensional data by the fusion of 5G edge computing and VR technology, high-definition images and accurate pattern recognition technology, edge computing and high-speed communication technology [37].

4.2. Digital twins in mining progress

Currently, the research of digital twin technology in the synthesized working face segment of extraction has made significant progress, and the literature [16] defines it as three aspects based on data and information interaction, physical working face and digital working face. Literature [39] realized three-level synergy and could accurately react to the real state by hybrid modeling of three-machine synergy, which meets the consistency requirements. Literature [40] completed the digital twin model related to mine production, which can be used as the core of intelligent mine knowledge service. Literature [41] achieves real-time monitoring and simulation of various operational parameters and conditions of the production system, optimizing configuration and safety. Thus, optimal configuration and college safe mining are achieved. At present, it has realized the application of digital twins in the underground centralized control room and ground dispatching center for the coal mining machine, hydraulic support, scraper conveyor, transfer machine, belt conveyor and other equipment in the working face, so as to achieve the remote control and visualization of the operating conditions monitoring and supervision.

Through fault diagnosis and analysis of the digital model of the equipment, the digital twin can provide maintenance recommendations and optimization solutions to reduce the equipment failure rate and improve the availability and maintenance efficiency of the equipment. The application framework of the mining face is shown in Figure 4. Literature [42] used discrete smooth interpolation (DSI) algorithm combined with accurate drilling survey data and seismic interpretation of layers to establish a three-dimensional geological digital model of coal mine, which provides geological guarantee for safe and efficient mining work. Literature [43] realizes the accurate reproduction of physical digging state in the digital digging process. Optimized decision-making assisted physical excavation control was also realized. Literature [44] realizes synchronous feedback and mapping interactive perception of wind flow at the outlet of the digging face, which is capable of real-time monitoring and intelligent prediction, autonomous decision-making and intelligent regulation.

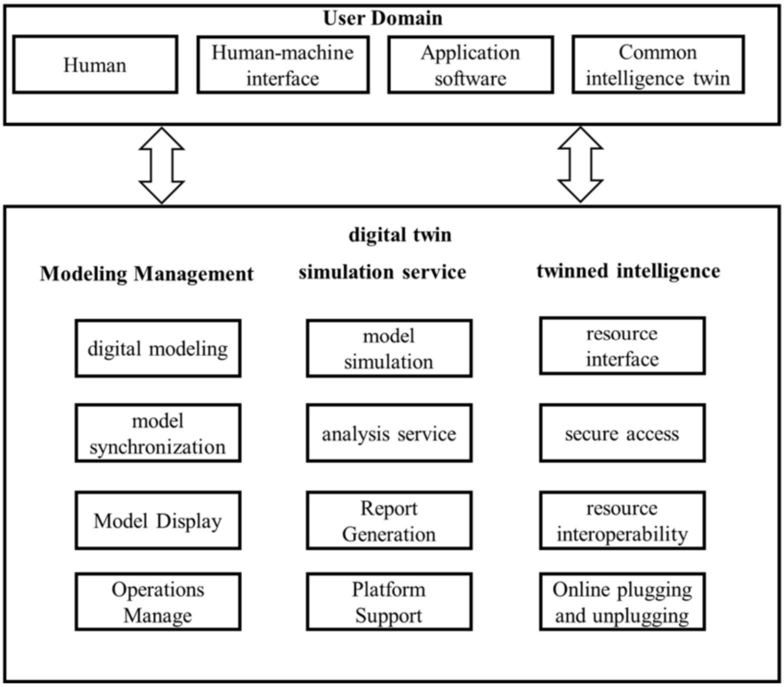

Figure 4. Extractive face application framework

5. Conclusions and outlook

Advantages of digital twins for mining equipment:

- Digital twin technology can help detect potential failures early, reduce the risk of equipment failure, and improve the reliability and safety of equipment by monitoring the status of mining equipment in real time, recognizing failure modes and making failure predictions.
- The use of digital twin technology can realize predictive maintenance of equipment, help repair equipment before failure, reduce equipment downtime, reduce maintenance costs and improve maintenance efficiency.
- The use of digital twin technology can simulate and optimize the performance of equipment, help improve equipment design and operating parameters, and improve the performance and productivity of equipment.

However, the accuracy and reliability of digital twins depend on the quality of the input data, the need for a large number of data inputs, the need for significant investment and resources, the existence of different standards and specifications, and the need to have advanced computer technology and data analysis capabilities to support. However, with the continuous development of digital twins, digital twin technology for mining equipment has a broad application prospect in improving equipment reliability, reducing maintenance costs, optimizing equipment performance, and promoting the digital transformation of the industry:

- With the rapid development of the Internet of Things and edge computing, mining equipment will be able to collect, store, and process large amounts of real-time data in a smarter way. Digital twins will be closely integrated with edge devices to realize real-time collection, analysis and feedback of device data, making digital twin technology more real-time and responsive.
- The digital twin will gradually have autonomous decision-making and collaborative optimization capabilities. Using artificial intelligence and machine learning algorithms, digital twins can analyze the data of mining equipment, achieve autonomous intelligent decision-making.
- Deep and augmented learning will bring more powerful data analysis and decision-making capabilities to the digital twin. By utilizing deep learning and augmented learning algorithms, digital twins can better understand and analyze data from mining equipment, extract useful knowledge and patterns from it, and make more accurate predictions and decisions.

Digital twin technology will bring more benefits and innovation to the mining industry.

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