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REGULAR PAPER

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Intelligent decision-making system for mineral processing production indices based on digital twin interactive visualization

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Abstract The multi-layer indices decision-making of complex industrial processes is the key to reducing costs and improving production efficiency. With the development of the Industrial Internet, a large number of industrial streaming data and intelligent algorithms have brought opportunities for optimizing plant-wide production indices. However, due to the strong dynamic and coupling of the production process, the intelligent system based only on the optimization algorithm cannot give practical data analysis suggestions and decision results, so a human–computer interactive visual analysis and index decision system are urgently needed. This paper combines multi-layer indices decision-making algorithms with 3D digital twin visual analysis technology to propose an intelligent decision-making system for mineral processing production indices based on 3D digital twin interactive visualization (DTIV). The DTIV system provides users a 3D digital twin modeling view from the production park, workshop, and equipment scenes. It adopts visualization technology that seamlessly integrates 3D and 2D to help users obtain indices decision input information and hidden data features from real-time stream data with different spatiotemporal data characteristics. In addition, the DTIV system also combines a multi-layer indices optimization decision-making algorithms engine and designs a human–machine interaction indices decision interface and indices decision execution visual analysis interface to improve users' production perception and decision-making ability. Through our collaboration with domain experts, carefully designed interviews, and prototype system evaluation in a beneficiation plant, the effectiveness and usability of the system have been proven.

Keywords Digital twin · 3D modeling · Indices decision-making · Interactive visualization · Mineral processing

1 Introduction

Mineral processing is a metal extraction process that extracts valuable minerals from the raw ores according to their physical or chemical properties (Hodouin et al. 2000; Chai 2009). Usually, the beneficial minerals

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are first liberated by comminution and size separation processes and then concentrated by magnetic separation and concentration processes. The overall performance of mineral processing production lines is specified in the global production indices, such as concentrate yield, concentrate grade, metal recovery rate, and concentration ratio. Indices decision-making has essential value in organizing and coordinating the production and operation activities of mineral processing. However, the production indices decision-making in mineral processing is a dynamic, nonlinear, and conflicting decision-making process. For example, pursuing high-grade ore requires increasing the degree of magnetic separation, leading to a low metal recovery rate as much valuable ore may be discarded. So optimizing the plant-wide production indices is the key to promoting the high-quality development of the manufacturing industry (Ding et al. 2017), and it is also one of the goals of Industry 4.0 (Henning 2013; Mihai et al. 2022).

In large-scale continuous industrial processes such as mineral processing, the relationship between global production indices and operational indices, as well as between functional indices and production process variables, is uncertain (Ding et al. 2017). The production decision-maker is unable to grasp effective indices decision-making information from massive industrial stream data and high-frequency production process data, resulting in reduced accuracy of manual decision-making. Therefore, it is necessary to develop a 3D digital twin interactive visualization (DTIV) intelligent system that serves the decision-making business of production indices.

The concept of digital twin (DT) first appeared in 2002 (Mihai et al. 2022), after a presentation entitled "Conceptual Ideal for Product Lifecycle Management". Under the promotion of the intelligent manufacturing environment, industrial DTIV intelligent systems have become one of the new directions for the future development of industrial intelligence. DT technology is crucial to mapping physical systems to digital models in information space using data interaction between geometric modeling, data models, and physical entities. The schematic diagram of the relationship between virtual space and physical space based on 3D DT is shown in Fig. 1. The Industrial DT utilizes new-generation information and communication technology (ICT) and industrial artificial intelligence algorithms to achieve data feature extraction and fusion of all production elements and achieve optimal production control in the production workshop.

Currently, the research methods for industrial production index decision-making based on DT can be roughly divided into intelligent algorithms and visual analysis methods. Intelligent algorithms can effectively provide an optimal solution or a set of superior Pareto frontiers, such as evolutionary optimization methods (Ma et al. 2006; Yu et al. 2011, 2013), or data-driven optimization methods based on deep learning (Yang et al. 2019; Ding et al. 2017) and reinforcement learning (Li et al. 2023a; Yang et al. 2022). The above algorithms have been widely applied in the decision-making of production indices in the process industry, saving a lot of manual work. However, assuming that the production process is in a steady state and the model parameters are deterministic, most existing work usually regards the production indices decision-making problem as a stationary single objective or multi-objective optimization problem or adopts the small data modeling method. It overlooks the dynamic environmental changes and operating conditions in the production process, making it challenging to optimize indices effectively.

On the other hand, visualization methods often appear together with manufacturing execution system (MES). This visualization system is often used to analyze the constraint information of production status and material properties (Gao et al. 2016; Li et al. 2023b) or analyze production management and decision-making (Sun et al. 2020; Jo et al. 2014; Heilala et al. 2010; Zhang 1996). This type of visualization method supports manual interaction to optimize production metrics, which is inefficient and time-consuming. In addition, these methods lack dynamic interactivity with real-time systems and do not support rapid response to sudden changes in equipment production status, which may lead to major production accidents.

To address the above issues, this paper proposes an intelligent decision-making system for mineral processing production indices based on DTIV, combining multi-layer indices decision-making algorithms with 3D visualized modeling technique, which improves users' production perception ability and indices decision-making ability from three aspects: what they see, what they think, and what they operate.

The contribution points are as follows:

- An online industrial data collection system has been established to ensure real-time stream data communication with the whole production line of mineral processing, which significantly improves the perception of the dynamic production environment. We have also built the cloud-edge collaboration system architecture, effectively integrating data servers, artificial intelligence computing platforms, and 3D digital twin systems to ensure the smooth operation of industrial dynamic modeling and indices intelligent decision-making business.

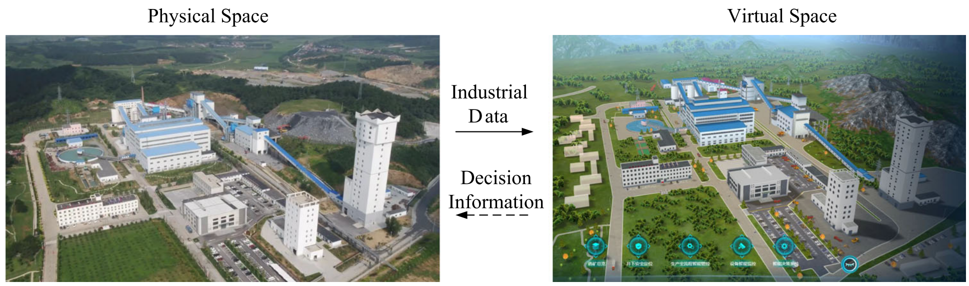

Fig. 1 The schematic diagram of the relationship between virtual space and physical space based on 3D digital twin

- We seamlessly integrate 2D and 3D technologies to achieve digital twin 3D visualization of the production park, workshop, and equipment. This paper maps physical workshops from multiple dimensions such as geometry, behavior, physics, and rules to construct a virtual space, achieving visual analysis of long process production processes and abnormal monitoring of internal equipment components.
- We deeply integrate multi-layer production indices decision-making algorithms and human-machine interaction systems. It includes indices decision-making modules based on expert knowledge and data-driven, decision-making implementation evaluation modules, and so on. The human–computer cooperation function of the system not only realizes the real-time interaction with the production system but also improves the rapid intelligent decision-making ability in the face of dynamic changes. At the same time, in the process of human–computer interaction, we record the information of human interaction and the opinions on the decision algorithm results to improve the accuracy of this system constantly.
- Case study using a beneficiation plant as application scenario, and conduct in-depth cooperation with field experts and enterprises. The functional evaluation of the prototype system on the production site has proven that our proposed indices decision-making solution can significantly improve people's decision-making ability and practical application value.

2 Related work

In this section, we present a detailed review of related work on 3D digital twin model construction, and visualization analysis.

2.1 3D digital twin model construction

Combining digital twin technology and 3D visualization makes the virtual world more closely aligned with the real world. 3D digital twin model construction technology is crucial in multiple scenarios such as smart cities, smart factories, and smart transportation (Oguz et al. 2006; Guo et al. 2021; Zhong et al. 2022; Yan et al. 2013). For example, Wei (2022) adopted browser/server (B/S) architecture to provide users with a real-time rendering of a three-dimensional scene of the city, including data mapping and intelligent services for traceability. It can be applied to traceability, monitoring, prediction, and management of cities. Lee et al. (2020) proposed a platform with movable dynamic data detection, reconstruction, and visualization steps. The users can visualize the past urban appearance and road situations in a 3D model. Pajpach et al. (2022) created an experimental workplace and an educational-development environment for the design of digital twin using interoperability and the 3D engine unity.

The digital twin in manufacturing essentially represents the imitation of equipment, systems, and processes. The most common use of digital twin is as 3D models in information systems. Fan and Yao (2023) designed and constructed the basic digital twin model of the scheduling process, the digital twin model of packing planning, and the digital twin model of scheduling process optimization. Joglekar et al. (2022) presented an interactive 3D visualization of a simPy-based DT of a natural surface mount technology printed circuit board line, which visualizes machine states, process flow, energy and throughput metrics in 3D. Mikhailov et al. (2022) also proposed that DT is a part of research increasing productivity and reducing operating costs in manufacturing and processes.

Although previous research on 3D digital twin modeling has been preliminarily applied in related industries, it only focuses on building 3D models with local devices as the main body and cooperating with data visualization to build digital twin platforms, lacking interactive operations. And their 3D modeling accuracy is not good enough, and the real-time performance of online data cannot meet production requirements. Compared with previous work, we propose a visual analysis scheme for 3D digital twin modeling from global to local. We have achieved interactive visualization with 360-degree rotation and device decomposition in the proposed system, with smooth graphics and precise details. This system combines domain knowledge and decision algorithms to support users to understand the required information quickly

2.2 Industrial stream data analysis

Industrial real-time stream data analysis is critical and widely used for production management decision-making closely tied to the key revenues of many industrial businesses (Muskan et al. 2022). Visualization analysis tools can improve the ability to process and summarize stream data and enhance the analytical ability of human experts through domain knowledge and data-driven algorithms (Ramanujan et al. 2017). For example, Sun et al. (2019) specifically designed a visual analysis system named PlanningVis for production planning business, which supports exploring and comparing production plans with three levels of detail. Gou et al. (2023) proposed a generic framework, namely the sliding sketch, which can be applied to many existing data stream processing solutions, enabling them to support queries in sliding windows. Weihua and Dong (2021) used the cite space software to analyze the current situation, hotspots, and trends of the industrial knowledge map research using the bibliometric analysis method. Kimani et al. (2013) took high-dimensional sensor stream data in industrial engineering as the research object for visualization and proposed a visualization environment based on the domain knowledge of industrial engineering visual information requirements and sensor stream data's temporal and multi-dimensional nature. Ma et al. (2010) proposed a fault detection statistical method based on statistical multivariate analysis and microarray visualization, which mines out key variables from a large set of variables. Bougouffa et al. (2019) provided 2D and 3D visualization solutions for the variability analysis of industrial automation system control software (conveyor modules), including tables and charts, chord diagrams, and three-dimensional forms of a spiral and tree structure. Wu et al. (2018) designed an interactive visual analysis system for industrial stream data, which supports real-time monitoring, detail inspection, and model updating. It can help managers and operators define the health status of online devices for effective equipment life-cycle condition monitoring. Industrial data is a typical stream of data with multi-scale and temporal characteristics. Inspired by the above technologies of stream data, we build an online industrial data collection system and combine the visualization analysis technology of industrial stream data to help users achieve efficient industrial multi-level indices decision-making business.

3 Overview

We introduce the background for the plant-wide production indices decision-making in the entire mineral process, analyze tasks to be completed in our 3D DTIV system, and derive the design requirements.

3.1 Decision-making description

Usually, the production management department of mineral processing organizes mineral processing production through production plans and scheduling instructions. The industrial data has typical time delay characteristics and multiple time scales due to different sampling periods. The dynamic characteristics are implied in the large amount of process data of high-frequency sampling and the production indices of low-frequency sampling. Besides, many production indices and control parameters in the beneficiation process are coupled with each other and have strong nonlinearity. Establishing accurate mathematical models through the metal balance principle and mechanical analysis approach is challenging.

Considering the different functions of each unit process in the whole production line of mineral processing, we divide the indices into three categories: global production indices, operational indices, and production process variables (Ding et al. 2017). The details are as follows:

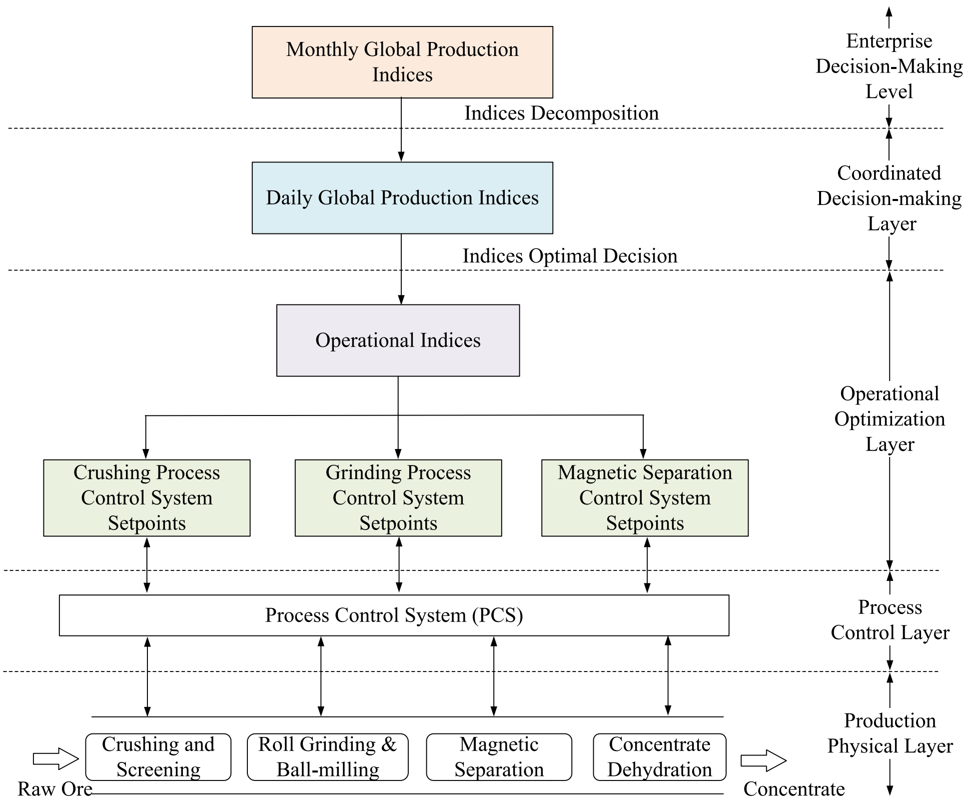

Fig. 2 Decision framework for plant-wide production indices of mineral processing

Global production indices The global production indices reflect the quality, yield, cost, power consumption, and other relevant production indices of the final product of the enterprise, such as concentrate yield, concentrate grade, metal recovery rate, and beneficiation ratio, etc.

Operational indices The operational indices reflect the quality, efficiency, and consumption of production equipment (or subprocess), such as the hourly operation rate, grinding grade, grinding particle size, waste rock grade, tailings grade, etc. The operational indices are usually obtained by human detection or statistical calculation.

Production process variable The production process variables refer to the high-frequency process data directly obtained by the process control system (PCS) through sensors or equipment controllers, including the setpoints for the process control system, input and output variables of the closed-loop control processes. They have strong coupling and high-frequency characteristics.

To optimize the manual-based decision-making process, we propose a hierarchical optimization structure of different time scales that aims at optimizing the plant-wide production indices of mineral processing, as shown in Fig. 2. The hierarchical decision-making structure for production indices of mineral processing includes five layers: enterprise decision-making layer, coordinated decision-making layer, operational optimization layer, process control layer, and production physical layer.

Usually, the decision-making department of the mining group preliminarily determines the target range of monthly global production indices $Q(t_m)$ based on the enterprise's annual production plan and the main equipment production capacity. Then, the $Q(t_m)$ will be distributed to the beneficiation plant. After obtaining the monthly global production indices $Q(t_m)$, the planning and scheduling department of the beneficiation plant needs to consider various influencing factors, such as the raw ore properties, workshop operation information, and maintenance and inspection information, to develop further the target range of daily comprehensive production indices $Q(t_d)$ for the entire production process. The production technicians decompose the $Q(t_d)$ into operational indices $r(t_h)$ for each unit process and control setpoints value y^* for the closed-loop control processes. After the decision results of these indices are determined, they will be released to the PCS.

In this paper, we seamlessly integrate the production indices optimization decision-making methods with the 3D DTIV system to achieve the plant-wide targets optimization of the entire mineral process.

3.2 Tasks analysis

Our main goal is to help decision-making experts improve their deep perception of production status and decision-making ability for the entire production process indices and provide them with a human–machine interactive visual analysis and indices decision-making intelligent system.

We worked closely with experienced experts in the mineral processing industry for approximately one year to obtain their feedback and design requirements for industrial decision-making. Through discussions with them, investigation work on-site, and literature research, we have proposed the following analysis tasks from our objectives.

T1: Visualize the plant-wide production indices of mineral processing The visual design should present the operational status, product quality, and the optimal results of production plans for the entire production line at different time scales. The data visualization can not only help domain experts analyze the execution progress of production plans but also provide auxiliary information needed for the decision-making of plant-wide production indices.

T2: Visual monitoring of equipment production status The domain experts can discover abnormal production status on time through the visualization system. The system can provide early warning and maintenance reminders for major equipment failures or non-optimal operating conditions.

T3: Provide a customized decision-making interface to achieve multiple-layer optimization of production indices within a single module The indices decision-making methods used for complex mineral processing often contain time-scale and space-scale decompositions of the global production indices. Based on the business scenario, developing a customized indices decision-making interface can improve manual decision-making efficiency.

T4: View the execution status of the plant-wide production indices After the indices' decision results are completed, the expert needs to check the actual execution progress and adjust the decision value of the plant-wide production indices for the next production cycle based on the results of the previous production cycle.

3.3 Design requirement

Based on these main tasks, we have summarized the following design requirements that our 3D DTIV system needs to support.

R1: 3D digital twin visual analysis at the park scenes and workshop scenes The 3D digital twin visual analysis system should highly restore the appearance and complex internal structure of the production unit processes and equipments in the beneficiation workshop, achieving the aggregation and visualization of decision information and industrial data **(T1)**. Besides, the system must display the spatial distribution of all workshop units and production data visualization **(T1)**. In large-scale continuous industrial processes such as mineral processing, displaying each workshop unit's production data and spatial distribution can effectively reveal intermediate production units' abnormal status and production capacity.

R2: Multi-scale industrial real-time stream data visualization Industrial real-time stream data visualization can visualize high-frequency dynamic data in real-time and enable users to see production process data and real-time operation status on the web without going to the production workshop and central control room **(T1)**.

R3: Monitoring visualization and fault diagnosis of equipment status Monitoring Visualization and Fault Diagnosis of Equipment Status should be able to directly display the abnormal status of internal equipment components, equipment operation data, and fault reasons to users through 3D equipment modeling visualization and visual interaction technology, enabling planners to accurately perceive the production capacity and operation status of core equipment, and provide accurate equipment constraint information for plant-wide production indices decision-making **(T2)**.

R4: Support interactive decision-making of the plant-wide production indices The AI decision-making system of the plant-wide production indices provides automatic intelligent decision-making for production indices and allows users to make secondary modifications to the decision results. In the smart decision-making mode, the user can obtain the latest indices decision input information in the indices decision interface and automatically receive indices decision results based on expert knowledge and optimization

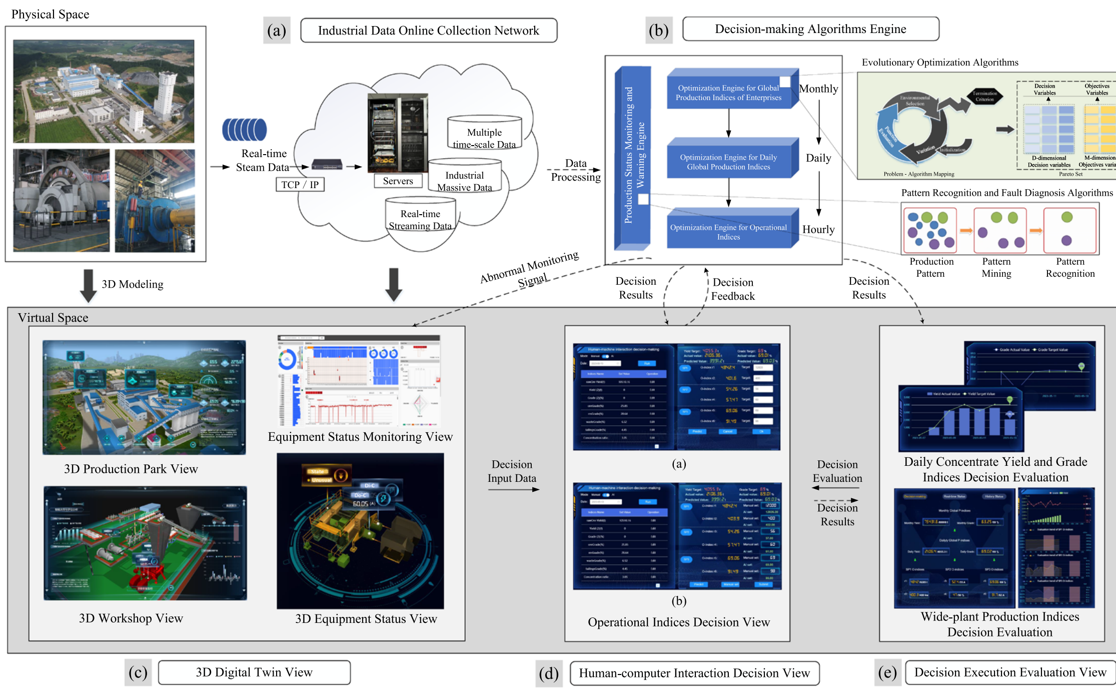

Fig. 3 The workflow of the 3D DTIV system. The system consists of three parts: data collection and storage, decision-making algorithms engine, and the establishment of virtual space with 3D visual modeling technology, which supports panoramic digital twin visualization and visual analysis, interactive decision-making of production process indices, and decision-making and evaluation of indices. **a** The industrial data online collection network built on industrial sites can collect, store, and preprocess real-time streaming data. **b** The indices decision-making algorithms engine is designed for multi-layer indices decision-making and status monitoring, forming an algorithm interface for visual analysis and decision-making systems. **c** Users obtain real-time production status, equipment capacity constraints, and expert knowledge decision-making input information from 3D View in the digital twin virtual space. **d** In the human-machine interaction decision view, the decision-making experts can obtain the initial decision results of the indices decision-making algorithms engine and adjust the decision results. **e** On the decision execution evaluation interface, the decision-making experts can view the completion or tracking status of the global production indices, operational indices, and control setpoints

algorithms. Under the artificial decision model, the user can modify inaccurate input information based on the intelligent decision results **(T3)**.

R5: Provide evaluation and analysis of production plan execution progress After the indices decision results are issued to the central control room of the beneficiation workshop, the user needs to obtain the execution progress of the production plan regularly **(T4)**, such as the degree of deviation between the actual value of the production indices and the decision value. By combining visual graphics of other data, this function can help users further understand the current production status and equipment production capacity to provide more effective decision values in the next production cycle.

3.4 Analysis pipeline

The workflow of the 3D DTIV system is shown in Fig. 3. The 3D DTIV system consists of three parts: data collection and storage, decision-making algorithms engine, and the establishment of virtual space with 3D visual modeling technology, which supports panoramic digital twin visualization and visual analysis, interactive decision-making of production process indices, and decision-making and evaluation of indices. Figure 4 shows the core interface and details of the developed system.

We focus on the integration and fusion of all elements, processes, and indices decision-making business data for multi-source and multi-scale information and massive industrial data in the beneficiation workshop. By combining 3D visual modeling technology, visual analysis technology, and ICT, we have digitized and mirrored the physical workshop to achieve 3D digital twin visualization at the park and equipment scenes. By effectively integrating park information resources, we combine DT visual analysis with equipment monitoring and diagnosis, indices prediction, and intelligent decision-making functions, providing comprehensive and accurate decision-making information.

Fig. 4 Intelligent decision-making system for mineral processing production indices based on DTIV. **a** Production park scene 3D digital twin. **b** Workshop scene 3D digital twin. **c** Indices intelligent Decision-making System. **d** 3D high-pressure roller mill equipment. **e** 3D ball mill equipment. **f** Equipment condition monitoring system

4 Technical preparation

4.1 Industrial data online collection technology

At present, there are two main ways to obtain industrial data, namely sensor detection and manual input. Usually, the instruments and equipments on the industrial production lines are directly connected to the I/O module of Siemens Programmable Logic Controller (PLC), and the process control system (PCS) can collect industrial data in real time. However, the PCS is not good at storing extensive industrial data for a long time. So we build an industrial server on the industrial workshop and perform data transmission and storage functions between the S7 communication protocol and PCS. Afterward, the end industrial server is connected to the public cloud server through communication transmission technology, and the collected data is sent in real time to the cloud *Wonderware* database for storage and provided to other systems. The data collection structure is shown in Fig. 3a. In addition, manual testing data must be manually input through the Manufacturing Execution System (MES) and stored directly in the cloud database. The production process variables are mainly collected from the PCS. The sampling frequency range of production process variables is 0.5s-5s. The operational indices and global production indices are usually sampled at the hourly level. The hourly sampling data is mainly collected from the MES. It should be noted that data communication and data collection need to ensure completeness, accuracy, and continuity.

4.2 Cloud-edge collaboration technology

The cloud-edge collaboration technology fully utilizes the industrial massive data and terminal computing capabilities on the edge server, in conjunction with industrial cloud servers for intelligent optimization and decision-making services, to efficiently achieve expert knowledge reasoning and industrial dynamic modeling Chai et al. (2021). When the accuracy of the edge model drops to the predetermined threshold, the model synchronization mechanism is activated to push the cloud model parameters to the edge server and update the edge model. The cloud-edge collaboration technology effectively combines data servers, artificial intelligence computing platforms, and 3D digital twin systems to ensure the smooth operation of industrial dynamic modeling and indices intelligent decision-making business. Specifically, it includes the use of cloud-edge collaboration technology and self-correction of models for decision-making and forecasting on the cloud server and edge server, respectively.

5 Visual design

The system mentioned in this paper adopts the software architecture of micro-service. A service implements a different feature or function, exposing various resources in RESTful API, and each independent micro-service is a small application. This paper constructs a distributed application system based on industrial cloud, where each service runs in an independent operating process and is independent of each other.

5.1 3D digital twin view

This paper focuses on the entire process line and production indices decision-making business of mineral processing, mapping the physical workshop from multiple dimensions such as geometry, behavior, physics, and rules, and developing a 3D digital twin scene. We realize the multiple-layer, temporal-spatial scale modeling from essential parts, equipments, production line, workshop area, and production park.

The 3D digital twin system adopts a front-end and back-end separation structure. The back-end system uses *SpringBoot* and *Mybatis* frameworks and constructs a standardized data access interface for the front-end system. The web front-end system adopts *VUE.js*, *three.js*, and *Blender* 3D modeling tools for seamless integration of 2D and 3D visualization technology. Based on effectively integrating various operational information, we reproduce the park environment, office buildings, workshop building distribution, as well as the whole production lines and equipments.

Production park scene 3D digital twin is shown in Fig. 4a The production park scene 3D digital twin view integrates various data resources and real-time production data to comprehensively monitor and analyze the production park's comprehensive operation, environmental space management, and production management and to unify the management of people, businesses, and materials in the park. Based on a 360-degree view of the production park, users can view production information of various short-process processes in a long-process production process to improve production decisions **(R1, R2)**. In addition, it also includes real-time monitoring of monthly global production indices for mineral processing, visual analysis of monthly execution progress **(R3)**, and abnormal warning of complex production conditions. And users can take measures timely to correct decision results **(R6)**.

Workshop scene 3D digital twin is shown in Fig. 4b The workshop scene 3D DT view is a highly reproducible internal structure of the entire beneficiation production line, which establishes a typical layered and long process detailed 3D modeling and visual analysis system based on the spatial location of each process and the flow direction of ore production. The functions include achieving 3D modeling of core equipment for mineral processing, real-time visualization of core process indices, and highlighting the abnormal status of production equipment in red **(R1, R2)**.

In Fig. 5a, hovering the mouse causes the workshop building border to highlight, and clicking on the digital building jumps to Fig. 5b, where the core equipment of mineral processing has been visualized and 3D modeling. Clicking on the equipment with the mouse will lead to Fig. 5c and d. The Users can quickly and intuitively obtain the global to local production information in this view.

5.2 Equipment status monitoring and diagnostic view

With the demand for the equipment condition monitoring system, this paper redesigns an equipment condition monitoring system (Fig. 4f) based on general function. With the help of visual analysis tools, this paper mainly designs the visual platform, which could display data from the general overview of all equipment conditions to a single equipment's details. For instance, the equipment scene 3D digital twin is shown in Fig 4d, e, which mainly restores the appearance, texture details, and complex internal structure of the equipment in virtual space, achieving high-precision and ultra-fine visual rendering. Moreover, we select reasonable visual expression forms and interaction technologies based on the attention needs of different equipment to visualize the main equipment's runtime state. For example, the equipment runtime state distribution monitoring view is shown in Fig. 6. In area C, we can see the state change timeline of the ball mill. The equipment started running after six days of shutdown at the beginning of the month, and then, there was a short failure and dictation. There are daily operation duration, fault duration, and hourly thermal diagrams under the status timeline. The hourly heat map shows that the fault occurred on day seven and lasted from 11 a.m. to 4 p.m. Area D shows the team information. The equipment utilization rates of the three teams were 89.87%, 83.61%, and 86.71%, respectively. Each team's daily equipment operation time statistics are also drawn in a histogram, and the specific details can be viewed by hovering the mouse.

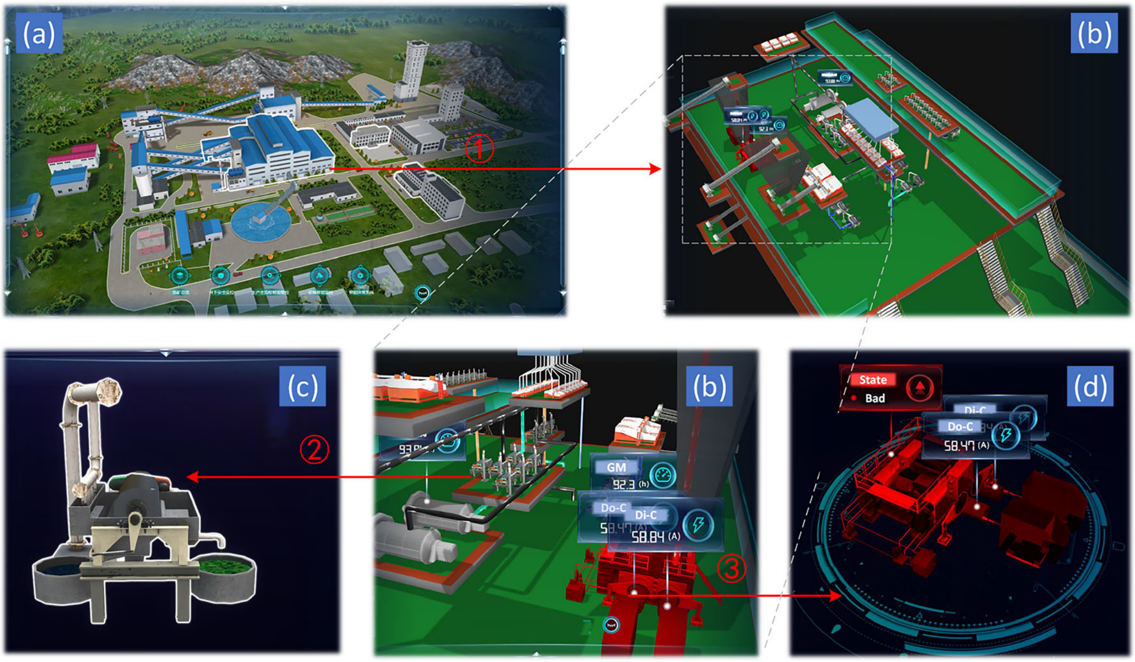

Fig. 5 3D DTIV view structure. The arrows in numbers ①, ② and ③ indicate the interface transition process. **a** Production park scene 3D digital twin. **b** Workshop scene 3D digital twin. **c** Magnetic separator equipment. **d** High-pressure roller mill equipment

The subsystem supports the accurate reproduction of equipment operation status, visualizes movement changes and the working status of internal core components, and provides real-time alarms for equipment operation abnormalities (such as faults, short circuit impacts, overloads, overheating, etc.), assisting managers in intuitively grasping the equipment operation status and discovering equipment safety hazards promptly **(R3)**.

5.3 Human–machine interaction decision-making view

The human–machine interaction decision-making view mainly includes five modules shown in Fig. 7. Figure 7a is the historical execution process of decision objectives, which uses a simple line chart and bar chart to show the completion of product output and quality in a week. Figure 7b is the decision-making information aggregation module, which records and displays decision-making information such as workshop production capacity, market demand, and feature analysis results. Users can switch between intelligent and manual decision-making modes by clicking with the mouse. Figure 7c is the intelligent decision-making panel for operational indices. Users can view the current completion status of decision objectives, predicted values of decision objectives, and planned and actual values of operational indices in this module. We uniformly use colors to distinguish: red represents the decision target value, yellow represents the real production value, and green represents the algorithm results. In intelligent decision-making mode, users can directly obtain the optimization results from the decision algorithm engine. In manual decision-making mode, users can manually modify the optimization results of operational indices based on decision information and deviations from decision objectives **(R4)**.

Figure 7d and e shows the execution visualization modules for decision objectives and decision variables, respectively. In the (d) and (e) views, we use the bar chart to display the cumulative tracking progress of concentrate production and use the line chart to display the completion of concentrate grade and operational indices in real time **(R5)**. In the (e) module, we use pink area shadows to highlight the production peak period. During peak periods, industrial electricity prices are expensive, so users should try their best to avoid allowing intermittent production equipment to operate during peak periods.

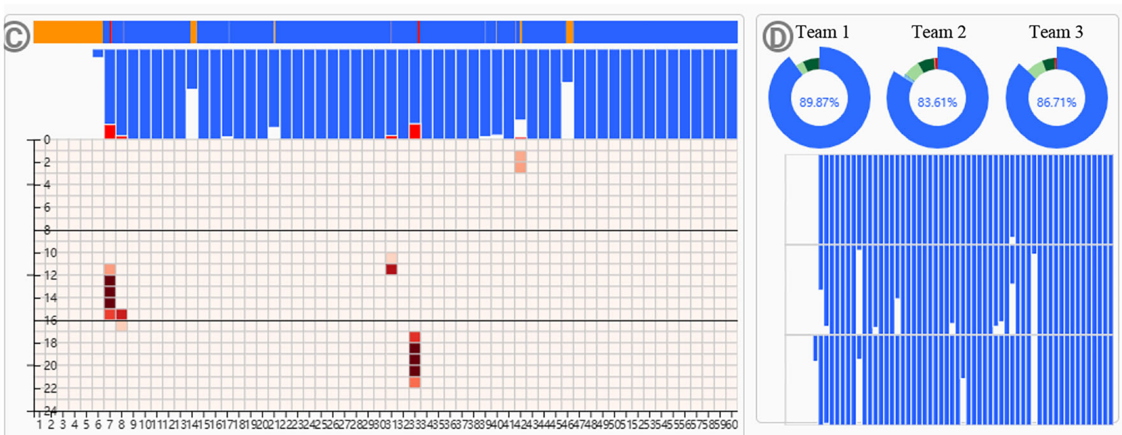

Fig. 6 The equipment runtime state distribution monitoring view of Fig. 4f

Fig. 7 Human–machine interaction decision-making view. **a** The historical execution process of decision objectives. **b** The decision-making information aggregation module. **c** The intelligent decision-making panel. **d** The execution visualization module for decision objectives. **e** The execution visualization module for decision objectives

Fig. 8 Multi-layer indices decision execution evaluation view

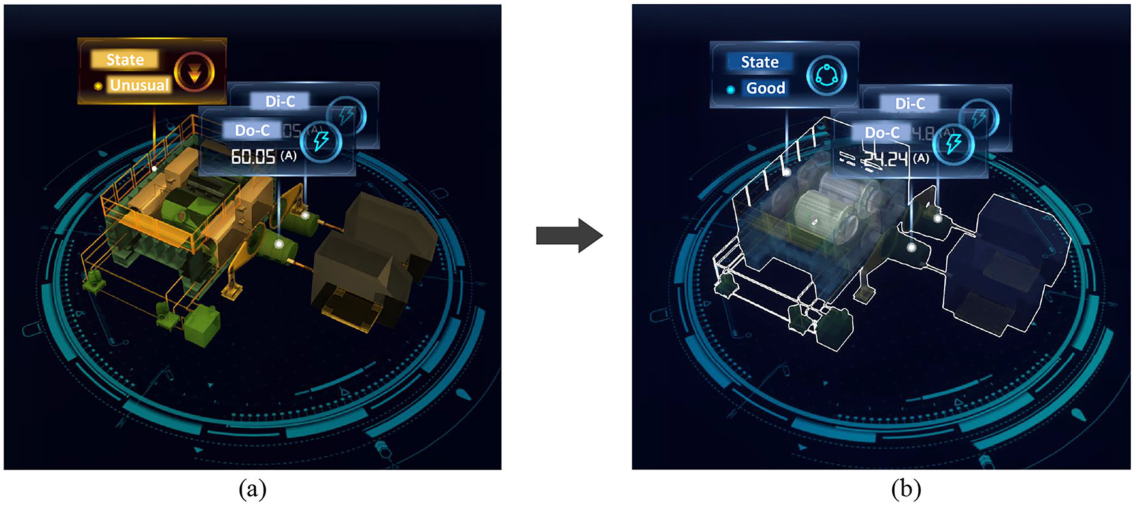

Fig. 9 Equipment status monitoring and diagnostic view. **a** Normal working state. **b** Abnormal working state

5.4 Decision execution evaluation view

The decision execution evaluation view of production indices visually monitors monthly global production indices, daily global production indices, and operational indices **(R5)**. This module uses intuitive bar charts and line charts to visualize the operation status of key production indices. For multi-layer indices decision results, the actual and target values are fused with the progress bar, as shown in Fig 8. When the target completion progress reaches 80%, the progress bar is green. When the target completion progress is less than 30%, the progress bar is red. In other cases, the progress bar is blue.

6 Case study with experts

6.1 Case exploration

To verify the effectiveness of the 3D DTIV system based on the multi-layer indices decision-making model, we developed a system prototype in the field of mineral processing. We provided the system to production decision-makers for prototype system evaluation. The use of this system involves three categories of people:

- Enterprise managers who optimize monthly global production indices.
- Workshop directors who make decisions on daily global production indices.
- Production operators who make decisions on operational indices.

Firstly, the user needs to judge whether the production condition is normal from the 3D digital twin view (Fig. 4) and equipment status monitoring and diagnostic view (Figs. 5, 6) to obtain effective decision information. Specifically, when the working status of two rollers of the high-pressure roller mill is abnormal, the 3D equipment model appears orange as an abnormal warning, as shown in Fig. 9a. When the mouse hovers over the 3D equipment model, users can view the operating modes of the two rollers in more detail. Figure 9b shows the view of two rollers generally working while the mouse hovers. Next, the user can view the decision input information automatically updated in the indices decision system view (Fig. 7). If the information aggregation is correct, the user selects the decision-making method and clicks the decision button. The result of the index decision will be sent to PCS. After the indices decision is issued, users can view the indices tracking curve and decision execution evaluation view (Fig. 7) in real time to monitor the current indices completion progress and determine whether to modify the decision-making results.

The optimization decision for the monthly global production indices of the beneficiation plant Xu et al. (2021) is to maximize the concentrate yield f_1, maximize the metal recovery f_2, and minimize the beneficiation ratio f_3. The decision variables are the raw ore yield ω, the raw ore grade α, the RM ore grade β_1, the waste ore grade β_2, the tailings grade β_3, the concentrate grade β_4, taking into account constraints such as the production capacity of the beneficiation plant, raw ore mining supply, and market demand. The

Fig. 10 The beneficiation plant for prototype system evaluation of the intelligent decision-making system

decomposition of monthly global production indices adopts a phased decomposition strategy based on rolling horizon optimization strategy Luo et al. (2017), which considers the internal and external production factors of decomposition days in each decomposition stage, obtaining the result of daily concentrate yield and concentrate grade. This system can decompose the monthly production indices into daily production indices for the next seven days and the recommended values for operational indices and control setpoints for the first day. The cloud-edge collaboration technology ensures model accuracy and training speed.

The intelligent decision-making system based on 3D DTIV has conducted data and information exchange with third-party systems such as the operational decision system, operational control system, and process control system for mineral processing.

The system has been tested in a mineral processing workshop, and the system function has been verified, which can reduce the labor intensity to a certain extent. The beneficiation plant for prototype system evaluation of the intelligent decision-making system is shown in Fig. 10.

6.2 Expert evaluation

To evaluate our goals, tasks, and design requirements, in addition to the **E1**, **E2** who are production managers in the mineral processing industry, we also invited four other external experts from different backgrounds (**E3–E6**). **E3** has 15 years of mineral experience in the mineral processing industry, **E4** has eight years of work experience in a Mining and metallurgy Research institute, and **E5** and **E6** have four years of production operation experience of front-line posts. All experts are familiar with the industrial indices decision-making process and production requirements. **E1**, **E3**, and **E4** have all published research papers on mineral processing production and indices optimization decision-making, while **E5** and **E6** have not conducted relevant research. After exploring and using the system, we conducted 30–40 minutes of one-on-one interviews with each expert and collected feedback from the six experts as mentioned above (**E1–E6**). They generally held a positive attitude towards the effectiveness of the 3D digital twin visualization system. Their feedback and suggestions are summarized as follows:

Effectiveness All six experts stated the production detail view was easy to understand since it adopted visual elements they were familiar with, such as the bar chart, the line chart, and the progress bar. **E3** commented, “The 3D DTIV system involves both the algorithm and our experience for production indices decision-making, which can significantly improve the indices decision-making efficiency.” In addition, **E1** has issued a proof of the prototype system evaluation effectiveness of the system, which states, “During the system evaluation period of this prototype system, the concentrate yield increased by 3%, the concentrate grade increased by 0.2%, the concentrate grade qualification rate increased by 8.3%." The successful functional evaluation of this system has achieved significant economic value.

Generalization After the field investigation and evaluation of the actual application effect of the system by the mining and metallurgy research institute where the expert **E4** work, **E4** said that "The system integrates intelligent decision-making mechanism, mine expertise, and 3D digital twin visualization technology, has done pioneering work in intelligent collaborative management and control of production indices and decision analysis." In the process of expert communication, **E4** stated, "This system is in line with the development direction of high-efficiency and intelligence in the mineral processing industry, and has the potential to be promoted to other mining enterprises."

Methodology Experts appreciate this system that combines automatic algorithms and domain knowledge to make indices decisions. The **E5** and **E6** stated that "Previous decision-making systems typically did not take into account all factors of actual production plans, and they typically needed to improve the results of the algorithm manually. And the decision-making system completely solves the previous problems." **E2** indicated that "When encountering special production conditions, the indices decision-making results provided by the algorithms engine can effectively guide decision-makers to make more accurate judgments. Moreover, the system can also learn some of their indices decision-making habits."

7 Conclusion and future work

In this paper, we combine multi-layer indices decision-making algorithms with 3D digital twin visual analysis technology to propose an intelligent decision-making system for mineral processing production indices based on DTIV, which maps physical workshops from multiple dimensions such as geometry, behavior, physics, and rules to construct a virtual space, achieving visual analysis of long process production processes and abnormal monitoring of internal equipment components. The DTIV system provides users with a 3D digital twin modeling view from the production park, workshop, and equipment scenes. It adopts visualization technology that seamlessly integrates 3D and 2D to help users obtain indices decision input information and hidden data features. In addition, the DTIV system also deeply integrates the multi-layer indices algorithms with human–computer interaction for visual decision-making and decision execution evaluation analysis. In the case study, the prototype system evaluation and expert evaluation have proven that the DTIV system can significantly improve people's decision-making ability and has practical application value.

In future work, we will consider adding more constraint information that affects indices decisions, such as energy supply, raw material properties, and market demand, and utilizing 3D digital twin visual analysis technology to enhance people's perception of industry information. In addition, we also hope to continuously enrich and strengthen the capabilities of optimization decision algorithm engines and integrate more production indices algorithms into 3D DTIV systems to solve more difficult industrial problems.

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