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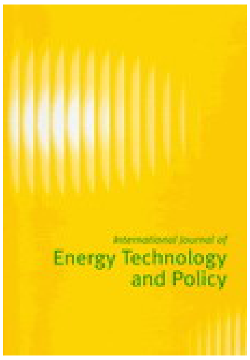


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# Intelligent monitoring method for variable working conditions in intelligent manufacturing systems under digital twin

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**Abstract:** This study presents a digital twin (DT)-based intelligent monitoring method for intelligent manufacturing systems (IMS) under variable working conditions. A five-dimensional DT architecture is designed to enable real-time data acquisition, synchronisation, and virtual-physical mapping. Linear regression is applied for data processing, enhancing monitoring accuracy. By constructing a DT virtual model of the production line, the system achieves dynamic monitoring and early anomaly detection. Experimental comparisons with genetic algorithm-based monitoring show the DT approach improves average monitoring accuracy by 8.47%, demonstrating its superior reliability, real-time performance, and potential for enhancing production quality and safety in complex, changing environments.

**Keywords:** intelligent monitoring; variable working condition; digital twin; intelligent manufacturing system; virtual model.

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## 1 Introduction

Intelligent manufacturing combines modern information technology, automation technology, modern management technology, and production technology to achieve intelligence in design, production, management, and customer service at all stages of the product cycle. Many enterprises have gradually started to apply IMS to improve production efficiency and quality when developing intelligent manufacturing (Wang et al., 2021a; Wang, 2019). Due to the influence of the working environment, equipment wear, and human factors, the working state of IMS can undergo various changes such as temperature, pressure, and vibration. This change would hurt production efficiency, product quality, and equipment lifespan. Variable working conditions and intelligent monitoring are real-time monitoring and analysis of process parameters in actual production, achieved through sensors, data acquisition systems, data analysis algorithms, and artificial intelligence. Real-time monitoring and analysis of the operating status of IMS is currently an essential task in the development of the manufacturing industry.

With the continuous maturity of digital technology theory, DT technology has made significant progress and has been widely applied in various professional fields (Gardner et al., 2020). It has tremendous application value in agriculture, construction, finance, and other fields. Digital twins have substantial real-time, scalability, and simulation capabilities. As a virtual copy that can generate physical objects or systems in the real world, DT can update and simulate them through real-time data, achieving high-precision virtual representation for comprehensive monitoring and analysis of objects. In intelligent monitoring, associating digital twin technology with real IMS can obtain real-time information on the working status of various components in the system. This can provide precise basis for subsequent monitoring and analysis, and has significant application value for improving the reliability and operational efficiency of IMS.

The contributions of this study are as follows:

1 A system architecture based on the five-dimensional structure of DT is proposed, including five dimensions: physical entity, virtual model, data, service, and connection. It enhances the integration and interoperability of the system, solves the problem of difficult data exchange between devices and systems in traditional systems, and provides structural support for building a high-precision and high-responsive IMS.

2 A linear regression model is used to model and analyse the collected IMS variable working condition data, which improves data processing efficiency and abnormality recognition capabilities.

3 By building a DT virtual model, real-time mapping and status tracking of the IMS production line are realised, thereby supporting the visualisation and intelligent monitoring of the production process under variable working conditions.

## 2 Related work

Intelligent monitoring of IMS operation status can detect and solve problems promptly, improving production efficiency and product quality (Shi et al., 2024; Aldrini et al., 2024). To ensure the stable operation of manufacturing systems under variable operating conditions, Wang et al. (2021c) proposed a deep interpolation architecture with three special layers based on the deep convolutional neural network architecture. He utilised interpolation principles and fusion units to achieve fault feature representation under unknown operating conditions. Finally, he verified through experimental research that the proposed monitoring method can effectively achieve reliable diagnosis of bearings under variable operating conditions. To stably monitor the operating characteristics of machinery under different operating conditions, Xing et al. (2020) proposed a distribution invariant deep belief network to directly learn the feature distribution under various working conditions from the original vibration data. He verified based on experimental results that deep belief networks can learn distribution invariant features through intelligent monitoring and have relatively ideal robustness. In order to monitor the working status of oil wells promptly, Wang et al. (2022b) combined big data technology with deep learning methods to dynamically monitor oil wells in different reservoirs, and developed an intelligent variable condition diagnosis system for oil wells. Practice has shown that this system can effectively improve variable operating conditions and achieve real-time diagnosis and alarm of variable operating conditions. Pham et al. (2020) proposed a new method for monitoring bearing faults under variable shaft speeds using acoustic emission signals to reliably diagnose bearing faults under variable operating conditions. This method can obtain as much information as possible from the time-frequency domain of bearing acoustic emission signals. According to experimental analysis, compared with existing monitoring methods, the proposed method has higher robustness. Although existing monitoring methods have specific stable monitoring capabilities for IMS variable operating conditions, their monitoring data still cannot meet the needs of real-time monitoring and analysis in manufacturing systems. The generalisation performance of existing methods is limited, making it difficult to adapt to changes in various working conditions, and the real-time performance is not strong enough, especially in the case of large amounts of data, which can easily cause delays.

The development of digital technology provides more possibilities for improving the real-time performance of intelligent detection of variable working conditions (Liu et al., 2024; Hossain et al., 2025; Bai et al., 2025). Qi et al. (2024) developed a digital twin monitoring system for large-scale complex surface processing by studying key technologies such as virtual twin model construction, multi-source data acquisition and transmission, and virtual-real mapping relationship construction. Finally, the feasibility and effectiveness of the dual system were verified through actual scenarios, providing a reference for workpiece processing process monitoring. Zi et al. (2024) proposed a new method for online monitoring of milling tool wear by digital dual-drive integrated learning. The DT data multi-level processing system optimises the signal feature data, and the milling cutter wear state and wear value is predicted in real-time by combining the integrated learning model. The two will verify each other. The results show that the prediction accuracy of the monitoring method exceeds 96%, and the prediction time is less than 0.1 s. Rojas et al. (2025) discussed the growing popularity of deep learning, reinforcement learning, and digital twins in anomaly detection and process optimisation, and proposed that future work should focus on real-time artificial intelligence and digital technology applications to accelerate the implementation of innovative maintenance solutions and ensure operational efficiency. To improve the real-time monitoring of variable operating conditions, Natesha and Guddeti (2021) used a fog computing architecture in industrial environments, extracting linear prediction coefficients and

Mel-frequency cepstrum coefficients from machine sounds and monitoring and fault diagnosis based on machine operating sounds. The experimental results show that fog computing can monitor machine equipment in real-time and quickly respond to machine changes in industrial environments. In order to meet the real-time monitoring requirements of variable working conditions in mechanical manufacturing, Zhou et al. (2011) has studied the new principles and methods of an intelligent monitoring and diagnosis system based on the combination of embedded technology and fibre Bragg grating sensor technology. He proposed embedded sensor signal processing and data transmission, which can meet the requirements of multi-parameter measurement, synchronous sampling, and long-term intelligent monitoring. Finally, experimental analysis shows the intelligent monitoring and diagnosis system has ideal real-time performance. To achieve industrial status monitoring and real-time process optimisation, Muthuswamy and Shunmugesh (2023) proposed intelligent detection of tool manufacturing status through digital twin technology through analysis and review of literature. He used artificial intelligence algorithms to predict tool performance to help establish an advanced intelligent factory ecosystem. To monitor the overall performance of machine equipment in real-time, Wang et al. (2021b) proposed a digital twin framework for traditional machine real-time monitoring. He connected isolated machines to interconnected systems and monitored their status in real-time, displaying the real-time status of the machines by creating a dashboard-based task centre. The final experimental results show that compared to existing methods with high design complexity, the intelligent monitoring method based on the digital twin framework has higher real-time performance. Digital twins can monitor and analyse real-time data of variable working conditions, achieving intelligent and real-time analysis of variable working conditions in manufacturing systems. Most studies still have certain limitations in terms of monitoring accuracy.

To improve the accuracy of IMS variable condition monitoring and effectively ensure the safety of the production and manufacturing process, this article combines DT technology to conduct effective research on IMS variable condition intelligent monitoring methods. It uses DT technology to construct a virtual model and simulate the production process of IMS under variable operating conditions, achieving real-time monitoring of the variable operating environment. To verify the effectiveness of DT technology in intelligent monitoring of IMS variable operating conditions, this article uses the XJTU (Xi'an Jiaotong University) – SY Bearing Datasets dataset as a sample. Experimental analysis was conducted from four aspects: monitoring accuracy, real-time performance, anti-interference performance, and fault detection rate. From the perspective of monitoring accuracy, compared with the GA-based intelligent monitoring method, the DT-based IMS variable condition intelligent monitoring method in this article has increased the average monitoring accuracy by 8.47%. In analysing real-time monitoring and anti-interference performance, the intelligent monitoring method of IMS under variable operating conditions based on DT has shown more ideal results. In fault detection, the monitoring method under DT technology has an average detection rate of over 90% under different data samples. In practical applications, the intelligent monitoring method of IMS under variable operating conditions based on DT can effectively improve monitoring accuracy, providing more reliable and comprehensive guarantees for the stable operation of IMS.

The innovation of this article lies in the use of DT technology to map physical space and virtual space in real-time, enhancing accurate perception and simulation of the operating conditions under all working conditions; by analysing the fault monitoring and diagnosis methods under complex and variable working conditions, the accuracy and speed of monitoring are improved, enabling smooth information exchange and thus enhancing the performance of IMS.

# 3 Intelligent monitoring method for variable working conditions in intelligent manufacturing systems

In the actual production process of IMS, equipment participation, workpiece status, actual production completion quantity, environmental factors, etc., all play a critical role in the system's production results (Liang and Rajora, 2018; Wang et al., 2022a). DT technology, based on data analysis, establishes models to reflect, simulate, and predict the status and behaviour of physical equipment in the actual production process in real-time (Wright and Davidson, 2020).

From a structural perspective, DT can be divided into five dimensions: physical objects, virtual models, network connections, and data and service system composition (Wu et al., 2021; Stark et al., 2019). As a tool for connecting the physical world and virtual space, DT, supported by data and service systems, can effectively support real-time monitoring, analysis, and decision-making services through the interaction between physical objects and virtual models.

## *3.1 Digital twin architecture*

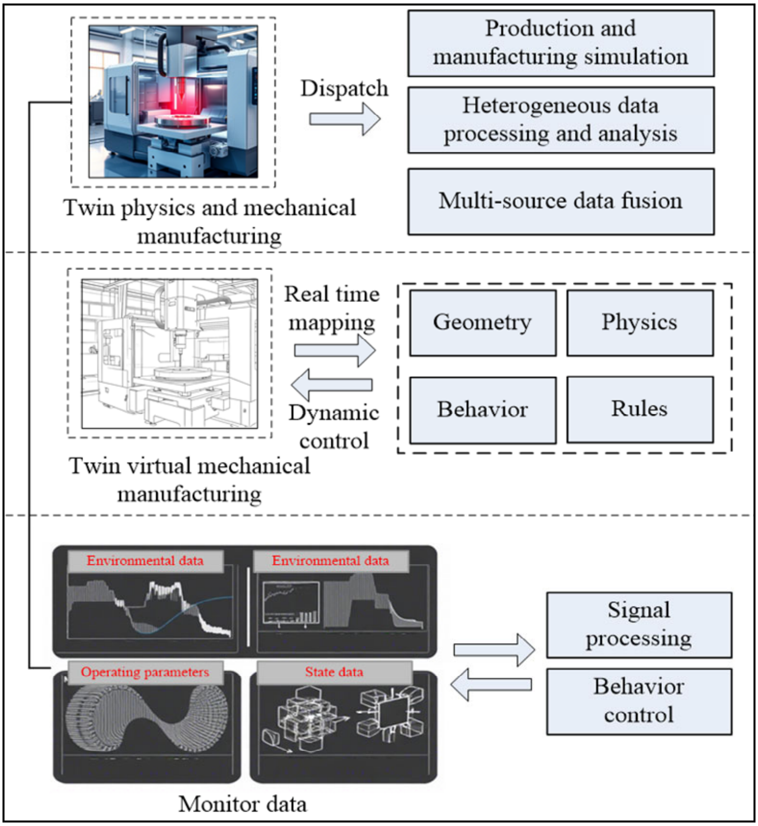
This article takes the machine equipment IMS as the research object and designs a digital twin architecture to achieve intelligent monitoring of IMS under variable operating conditions. IMS operation is a complex dynamic process that integrates multiple characteristics such as comprehensiveness, systematicity, and complexity. Figure 1 shows the architecture of the digital twin system in this article.

Figure 1 indicates that the architecture of digital twins consists of four levels, with data and information transmission and interaction between each level mainly achieved through iterative mapping.

### *3.1.1 Physical layer*

The physical layer is a prerequisite for reflecting, simulating, and predicting the actual production process of IMS. IMS has a dependency relationship between production tasks, which requires scheduling in a particular order and time window (Fu et al., 2021). Therefore, in actual production, it often involves multiple heterogeneous data sources. In addition to simulating IMS conventional production and manufacturing, the physical layer can also perform parallel processing and analysis on numerous heterogeneous data sources such as environmental data, equipment data, and material data. Under the instructions of programmable logic controllers, the physical layer can efficiently process, load and unload workpieces, and detect product features. It can classify and integrate monitoring data by combining sensor networks, radio frequency identification devices, and other devices, utilising relevant protocols of the internet of things (Nica and Stehel, 2021). In data processing, the physical layer can rely on this mechanism to achieve multi-source data fusion in the IMS production process, providing a data analysis basis for IMS variable condition monitoring.

**Figure 1** Digital twin architecture (see online version for colours)




### *3.1.2 Virtual model layer*

The digital twin model has the same structure and behaviour as the actual system or process and can reflect the state and operation of the actual system in real-time (Zheng et al., 2019, 2022). The virtual model layer includes four levels: geometry, physics, behaviour, and rules, which are mainly mapped in real-time from physical entities to virtual entities through the collaboration of professional software. At the geometric level, virtual models are built based on the actual production line layout of IMS, and are mainly used to analyse and describe information such as the shape and size of equipment in the production line. At the physical level, virtual models are built based on IMS physical entity attributes. They mainly analyse and describe material features, constraint conditions, and other information in variable working condition entity elements. At the behavioural level, virtual models are used primarily to analyse and describe internal operating mechanisms based on the interaction relationships, influencing factors, and working principles of IMS mechanical equipment. In the rule hierarchy, virtual models are built based on IMS material transmission and transformation, information exchange and control. They are mainly used to analyse and describe physical device elements' operation and evolution laws.

### *3.1.3 Data layer*

The data layer is the key to real-time monitoring of IMS variable operating conditions. It mainly covers physical spatial information such as mechanical equipment operating parameters, status data, and environmental data. In monitoring IMS variable operating conditions, the data layer in the DT architecture can conduct real-time analysis of updated mechanical equipment operating parameters, status data, and environmental data, providing more accurate information for IMS variable operating condition production decision-making. According to the twin data attributes, the datasets in the data layer are divided into two categories: the device data analysis comparison dataset (a set of all device analysis rules) and the device operation status dataset. Equipment data analysis and comparison is a set of equipment performance indicators, fault diagnosis rules, and prediction models, with a data structure shown in Table 1. Equipment data analysis and comparison are mainly used to quickly identify equipment problems and assist in providing corresponding solutions. Equipment operation status data refers to all equipment operation status data containing multiple sets, with each device's operation status data being a group. This mainly includes real-time operating status and historical equipment operating data. By analysing these data, equipment anomalies and faults can be detected, and the data structure is shown in Table 2.

**Table 1** Device data analysis and comparison dataset data structure

| *Field name* | *Descriptive* | *Data type* | *Length (bytes)* |
|---|---|---|---|
| Device identification | Number identification of the mechanical device | Varchar | 50 |
| Device name | Name of mechanical device | Varchar | 50 |
| Device category | Types of mechanical device | Varchar | 50 |
| Device used date | Date of use of device in intelligent manufacturing systems | DateTime | 20 |
| Update date | Update the date of the device in the intelligent manufacturing system | DateTime | 20 |
| Device data content | Device operation data parameter content | Varchar | 100 |

**Table 2** Data structure of equipment operation status dataset

| *Field name* | *Descriptive* | *Data type* | *Length (bytes)* |
|---|---|---|---|
| Device identification | Number identification of the mechanical device | Varchar | 50 |
| Device name | Name of mechanical device | Varchar | 50 |
| Device category | Types of mechanical device | Varchar | 50 |
| Device operation time | The running time of mechanical devices in intelligent manufacturing systems | DateTime | 20 |
| Timestamp | Corresponding stored timestamp | DateTime | 20 |

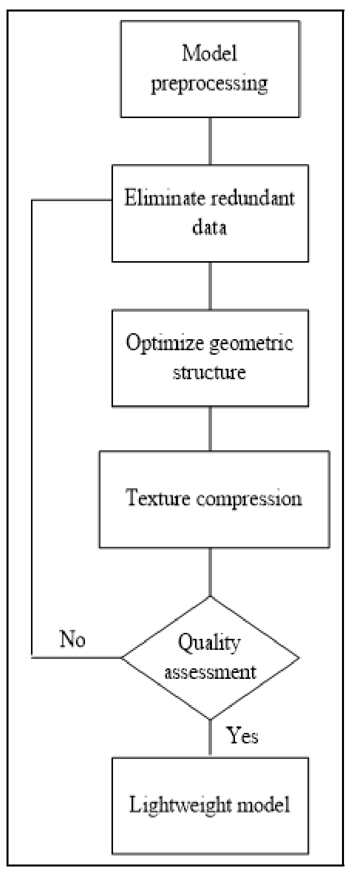
In Table 1, the data structure of the device data analysis comparison dataset mainly includes device identification, device name, device category, device usage date, update date, and device data content.

In Table 2, the data structure of the device operation status dataset mainly includes device identification, device name, device category, device operation time, and time stamp.

### *3.1.4 Service layer*

The service layer is an essential support for simulating and mapping IMS variable operating conditions. At the service layer, most specialised virtual service components require separate scripts to define the behaviour and logic of the elements. This article divides virtual service components into signal processing and behaviour control. The signal processing component is used to monitor the device's driving data. The signal processing component performs corresponding operations when the data changes and reaches the set threshold or above. Behavioural control monitors various production activities under variable operating conditions of IMS in real-time through control devices, thereby interacting with the functions of the physical layer.

**Figure 2** Model lightweight processing



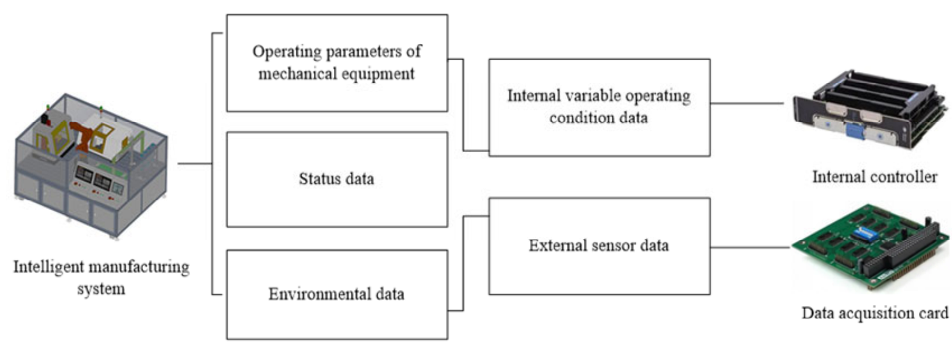
To analyse the production process under variable operating conditions of IMS and simulate the behaviour patterns of physical space, this article establishes a virtual model based on the DT architecture. The virtual model is established using a grid model, and lightweight processing is performed on the virtual model based on multiple influencing factors of production results in the IMS system, as shown in Figure 2.

In Figure 2, the redundant data present in the model is first eliminated, followed by optimisation of its geometric structure and texture compression. Finally, the quality of the model is evaluated. If the quality requirements are met, the lightweight processing is completed. If the requirements are unmet, the redundant data elimination step is returned for repeated processing. Lightweight processing of DT models can effectively shorten the time for model loading and information transmission, accelerate the computational speed of digital twins, reduce their latency, and improve the real-time performance of intelligent monitoring.

## *3.2 Data collection and processing under variable operating conditions*

Collecting variable operating conditions data is a prerequisite for achieving intelligent monitoring of IMS variable operating conditions. The data collection objects include mechanical equipment operating parameters, status data, and environmental data. It specifically includes internal data such as shaft position and coding obtained from mechanical equipment under IMS variable operating conditions and external sensing data such as mechanical equipment vibration and current signals. The process is shown in Figure 3.

**Figure 3** Data collection under variable operating conditions (see online version for colours)




The collection of variable operating condition data mainly includes the collection of three types of data, the first being the operating parameters of mechanical equipment, the second being the status data, and the third is environmental data. In Figure 3, based on the variable operating conditions in the IMS system, the continuous data obtained is a set of time series data geometrically arranged on the same time series. It is a continuously changing and identical parameter, and its changes over some time also have a significant temporal correlation. On this basis, the collected data is treated as a function that changes over time, and a univariate linear regression model is constructed (Deshmukh et al., 2023):

$$D' = I + ST \tag{1}$$

The definitions of each variable are shown in Table 3.

**Table 3** Interpretation of variables in univariate linear regression model

| *Sequence* | *Variable* | *Meaning* |
|---|---|---|
| 1 | $T$ | Data collection time |
| 2 | $D'$ | The data value corresponding to the collection time |
| 3 | $I$ | Line intercept |
| 4 | $S$ | Line slope |

According to Table 3, set consecutive $n$ IMS terminal nodes as a dataset with a certain deviation from the model, and record this dataset as $D_a = \{(T_1, D_1), (T_2, D_2), \ldots, (T_n, D_n)\}$. It can be seen as a linear function, with the independent variable being the sampling time $T$ and the dependent variable being the sampled data value. Set $T_i$ $(0 < i < n + 1)$ as the data sampling interval, starting when data $D_1$ is collected. Set the time corresponding to collecting data $D_{i+1}$ as $\sum_{j=1}^{i} T_j$, and obtain the model parameters through the least squares method (Lakshmi et al., 2021; Daniya et al., 2020):

$$\begin{cases} S = \dfrac{-D_1\left(D_1 - \bar{D}\right) + \sum_{i=1}^{n-1}\left(\sum_{j=1}^{i} T_j - \bar{T}\right)\left(D_i - \bar{D}\right)}{T^{-2} + \sum_{i=1}^{n-1}\left(\sum_{j=1}^{i} T_j - \bar{T}\right)^2} \\ I = D' - S\bar{T} \end{cases} \tag{2}$$

Among them, the time the formula expresses average $\bar{T}$ and data average $\bar{D}$:

$$\begin{cases} \bar{D} = \dfrac{1}{n}\sum_{i=1}^{n} D_i \\ \bar{T} = \dfrac{1}{2}\sum_{i=1}^{n-1} T_i \end{cases} \tag{3}$$

After collecting internal and external data under variable operating conditions, the data is preprocessed. To reduce the impact of different data differences on the analysis results, the collected work status data can be converted into a unified format data unit and the two data types can be merged. The data types and lengths obtained for different devices in IMS are different, which makes it impossible to process according to unified specifications. In the preprocessing process, this article uses a universal data unit format to enable more comprehensive and stable transmission and accurate data analysis at all levels.

Firstly, based on the data parameter sorting table of the corresponding equipment, this article combines internal data with external data to form a comprehensive data content. It then adds it to the standard data unit format. It forms a complete data element by supplementing control information such as device type, data type, data content, and data description. Finally, based on the corresponding comparison table, the corresponding monitoring areas were analysed to obtain the required dynamic parameters for variable operating conditions, and they were applied to the entire IMS variable operating conditions scenario to achieve intelligent monitoring.

### 3.3 Intelligent monitoring

Intelligent monitoring based on digital twins is a simplified virtual model abstracted from the actual production process through digital twin technology (Xie et al., 2019; He et al., 2018) The virtual model is established for processing *n* workpieces on *m* mechanical equipment under IMS variable operating conditions. In this model, the constraints for the workpiece and equipment are mainly:

1 on the same machine, the same workpiece cannot be reused

2 the task processing process cannot be interrupted during execution

3 each processing process is independent of each other

4 the processing time and order required for each process are known.

Based on constraints, real-time monitoring of IMS operating conditions is carried out, with the goal of maximum processing completion time, delivery time, and inventory, to monitor the system's operational status in real time. Set the objective function as:

$$f_t = \begin{cases} p_{rl} - g_{rl} + K(1 - x_{rl}) \geq p_{rl} \\ p_{bl} - p_{rl} + K(1 - x_{rl}) \geq p_{bl} \\ p_{rl} \geq 0 \; (r = 1, 2, \ldots, n; l = 1, 2, \ldots, m) \end{cases} \tag{4}$$

The definition of the objective function formula variable parameters is shown in Table 4.

**Table 4** Definition of objective function formula variable parameters

| *Sequence* | *Variable* | *Meaning* |
|---|---|---|
| 1 | $f_t$ | Objective function |
| 2 | $p_{rl}$ | The processing end state of workpiece *r* on machine *l* |
| 3 | $p_{bl}$ | The processing end state of workpiece *b* on machine *l* |
| 4 | $g_{rl}$ | The initial processing state of workpiece *r* on machine *l* |
| 5 | $K$ | A sufficiently large positive number |
| 6 | $x_{rl}$ | Indicator variables |

**Table 5** Coordinate scene variables

| *Sequence* | *Variable* | *Meaning* |
|---|---|---|
| 1 | $o$ | Target monitoring object |
| 2 | $c_i^o$ | Characteristic points of target monitoring objects |
| 3 | $(L_{i,x}^o, L_{i,y}^o, L_{i,z}^o)$ | Local coordinate system |
| 4 | $o_a$ | Centroid |
| 5 | $c_i^s$ | Scene feature points |

According to the formula variables in Table 4, based on the feature points of the tested object under changing operating conditions, the local coordinates from each feature point to the marker point are used as vectors, and the coordinate scene variables are set as shown in Table 5.

According to Table 5, in the overall coordinate system of the model, the vector from the feature points to the centroid is the main vector:

$$v_{i,G}^{o} = o_a - c_i^{o} \tag{5}$$

In the IMS monitoring process, in order to ensure the stability of vectors in various coordinate systems, the DT virtual model is used to convert vectors into local coordinate systems, and the calculation formula is expressed as (He et al., 2021; Cai et al., 2018):

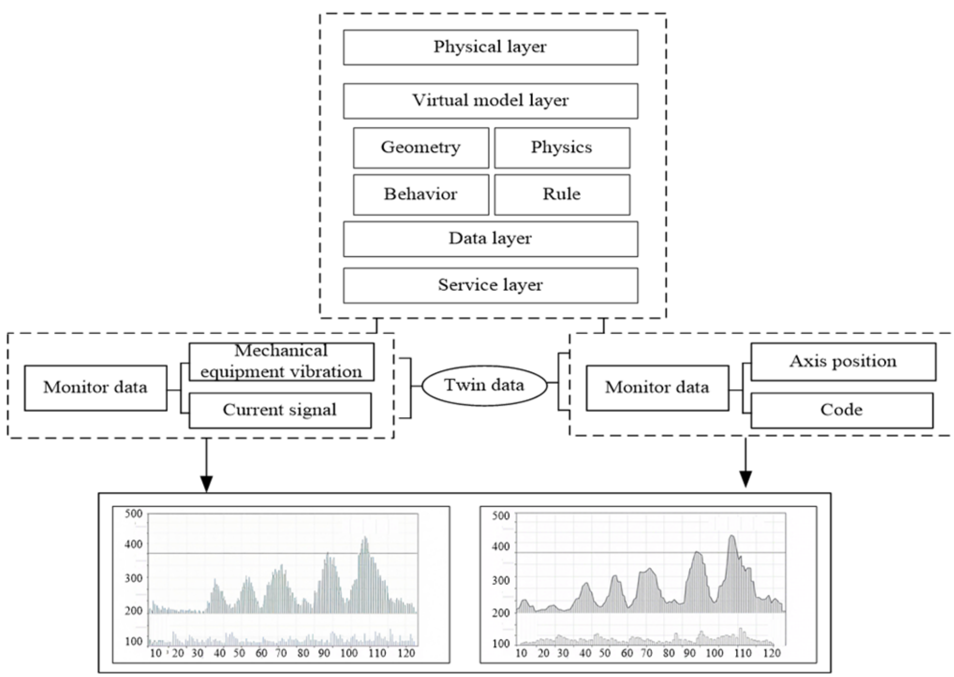
$$v_{i,L}^{o} = W_{GL}^{o} \cdot v_{i,M}^{o} \tag{6}$$

The definition of a variable in the vector transformation formula is shown in Table 6.

**Table 6** Explanation of variable in vector transformation formula

| *Sequence* | *Variable* | *Meaning* |
|---|---|---|
| 1 | $v_{i,L}^{o}$ | Vector local coordinates |
| 2 | $W_{GL}^{o}$ | Conversion matrix from global coordinate system to local coordinate system |
| 3 | $G$ | Global Coordinates |
| 4 | $L$ | Local coordinates |
| 5 | $s$ | Monitoring scenario |

**Figure 4** IMS intelligent monitoring under DT



According to Table 6, the composition of the IMS variable operating conditions digital twin is built into the monitoring scenario $s$ in the form of $(o, c_i^o, v_{i,L}^o)$.

On this basis, according to the system's functions, the implementation of the intelligent monitoring function is divided into two main modules: real-time monitoring and historical monitoring. The real-time monitoring function is mainly used in IMS to monitor mechanical equipment under variable working conditions in real-time and to analyse and diagnose its operating status in real-time. The historical monitoring function reproduces the past operating parameters of mechanical equipment under variable operating conditions, achieving reanalysis and fault diagnosis of the entire variable operating environment of IMS. As shown in Figure 4.

In real-time monitoring, logical operations are performed on real-time data to map it to the entities of the IMS system in real-time. During IMS operation, real-time mapping of device operating parameters, status data, and environmental data is carried out through the DT virtual model. It can be switched from any angle as required. Based on real-time production data driven, DT can accurately express the manufacturing process of products, and monitor the starting and ending states of workpieces, thereby achieving the evolution of workpieces from zero to the final state in IMS.

## 4 Digital twin intelligent monitoring experiment

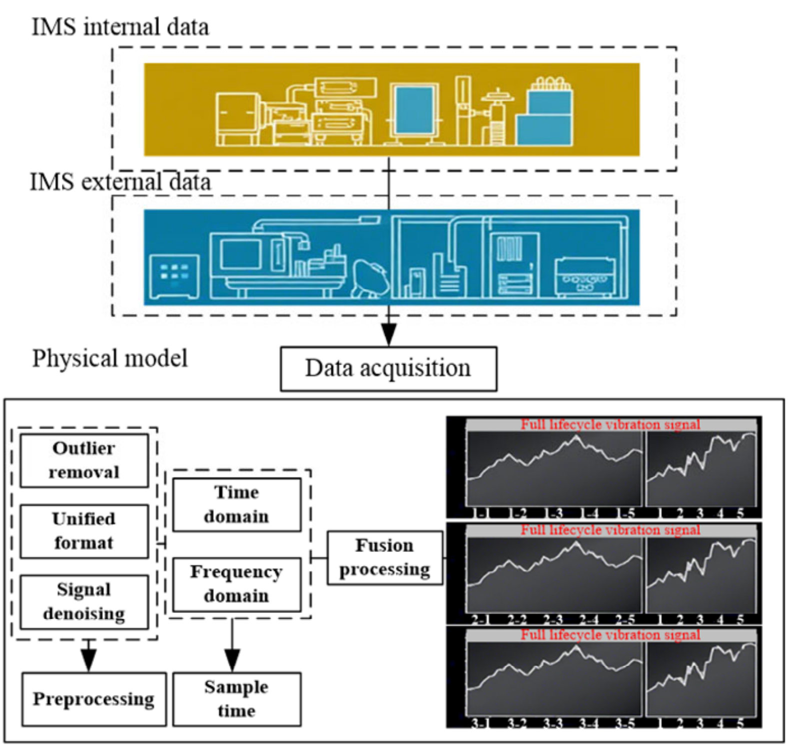
To verify the effectiveness of the DT-based IMS variable condition intelligent monitoring method, this article conducted an intelligent monitoring experimental analysis from monitoring accuracy, real-time performance, anti-interference, and fault detection rate and compared it with the monitoring method based on genetic algorithm (GA). This article uses the XJTU-SY Bearing Datasets dataset as the sample set for intelligent monitoring experimental analysis. XJTU-SY Bearing Dataset is currently the most commonly used dataset for mechanical equipment monitoring. It includes the working parameters of rolling bearings under various working conditions, covering normal working conditions and different failure modes. This dataset has detailed data annotation and various working conditions. The data is collected by acceleration sensors, covering vibration signals under normal conditions and fault conditions, as well as the operating status data of rolling bearings under various working conditions. It is suitable for evaluating fault detection rate, monitoring accuracy, real-time performance and anti-interference performance under variable working conditions in this paper. It is a practical and representative dataset. Therefore, this article uses it as a test sample to test the effectiveness of monitoring methods. This dataset contains the full life cycle vibration signals of 15 rolling bearings under three different operating conditions, as shown in Table 7.

In the dataset of Table 7, three types of variable operating conditions were designed, each with five bearings. The sampling frequency was set to 25.6 kilohertz, the sampling interval was 1 minute, and each sampling time was 1.28 seconds. The dataset corresponds to three different operating conditions, with five types of datasets set for each operating condition. The total number of samples constructed under different operating conditions also varies. The application of digital twin architecture is shown in Figure 5.

**Table 7** Dataset composition

| *Variable operating condition* | *Dataset* | *Number of samples* |
|---|---|---|
| Variant condition 1 | 1–1 | 123 |
| | 1–2 | 161 |
| | 1–3 | 158 |
| | 1–4 | 122 |
| | 1–5 | 52 |
| Variant condition 2 | 2–1 | 191 |
| | 2–2 | 161 |
| | 2–3 | 533 |
| | 2–4 | 42 |
| | 2–5 | 339 |
| Variant condition 3 | 3–1 | 2,538 |
| | 3–2 | 2,496 |
| | 3–3 | 371 |
| | 3–4 | 1,515 |
| | 3–5 | 114 |

**Figure 5** The application of digital twins (see online version for colours)



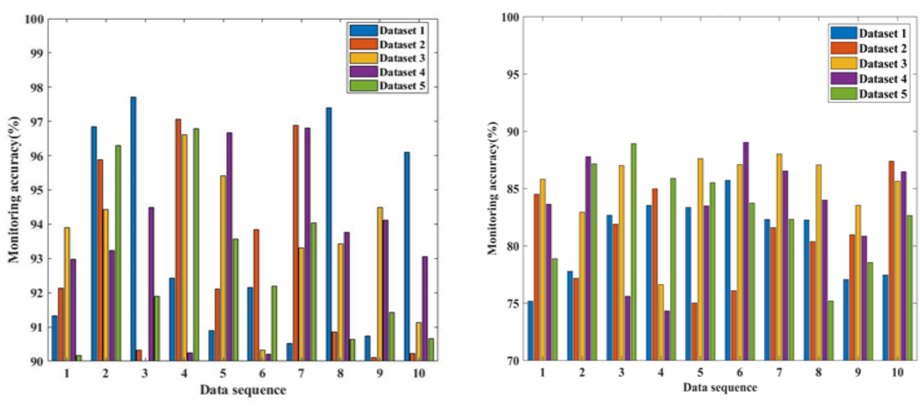
## *4.1 Monitoring accuracy*

In IMS, accurate monitoring of mechanical equipment operating parameters, status data, and environmental data has a crucial impact on product quality. In the analysis of intelligent monitoring experiments, this article randomly selects ten types of sample data from each dataset type. This article analyses the application of DT-based monitoring methods and GA-based intelligent monitoring methods. In the analysis of monitoring accuracy, this article takes the positioning error as the difference between the monitored abnormal position and the actual abnormal starting position under the marked variable working conditions. Assuming that the anomaly time index marked by the monitoring method is $t_a$, and the actual fault time index is $t_r$, the positioning error $\varepsilon$ is represented by:

$$\varepsilon = t_a - t_r \tag{7}$$

The magnitude of this result directly reflects the detection accuracy of the monitoring method for abnormal events. The fluctuation amplitude of positioning error under variable operating conditions demonstrates the adaptability of monitoring methods to complex environmental changes. Suppose the amplitude of the positioning error change is small. In that case, it verifies that the monitoring method has higher stability and accuracy in complex working conditions, thus proving its superiority in intelligent manufacturing systems. The smaller the positioning error, the more accurately the method can determine when the abnormality occurs, reflecting its effectiveness in improving accident response and handling. According to Formula 7, 20 repeated experiments were conducted, and the final monitoring accuracy results are shown in Figure 6.

**Figure 6** Monitoring accuracy results, (a) the accuracy of the DT-based monitoring method (b) the accuracy of the GA-based monitoring method (see online version for colours)



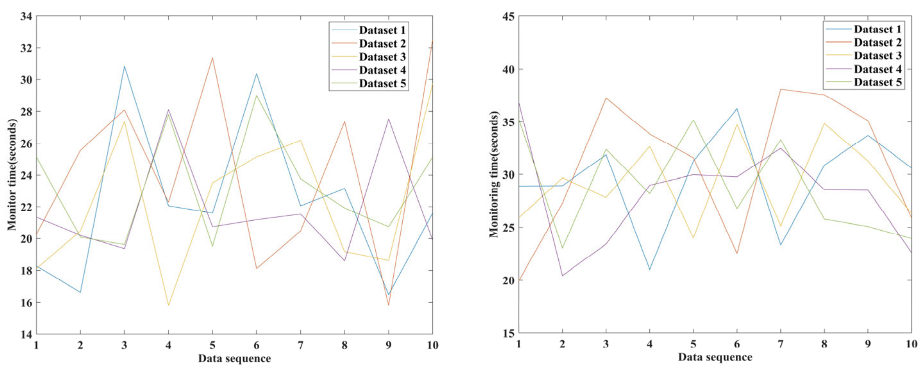

(a) (b)

From the monitoring accuracy results in Figure 6, the DT-based monitoring method results are more ideal. In Figure 6(a), the average monitoring accuracy results of the IMS intelligent monitoring method based on DT under different datasets were about 93.61%, 92.94%, 93.30%, 93.56%, and 92.76%, respectively. The average monitoring accuracy was above 90%, and the highest average accuracy was 93.61%. In Figure 6(b), the average monitoring accuracy results of the GA-based intelligent monitoring method under different datasets were about 80.74%, 81.01%, 85.14%, 83.18%, and 82.89%, respectively. The average monitoring accuracy was only above 85.14%. From the comparison results, compared to the highest average monitoring accuracy of the GA-based intelligent monitoring method under different datasets, the IMS variable working condition intelligent monitoring method based on DT in this article has increased by 8.47%.

### *4.2 Real-time monitoring*

In the actual operation process of IMS, real-time monitoring can help management personnel detect system abnormalities promptly, such as equipment failures and process abnormalities. Through real-time monitoring, problems can be quickly identified, and corresponding measures can be taken to avoid production delays or quality issues. To effectively analyse the real-time performance of the detection method, this article randomly selects ten types of sample data from different datasets, and other sample data correspond to different abnormal states of mechanical equipment under IMS variable working conditions. This article applies different monitoring methods to monitor the equipment status and compares the time spent identifying abnormal states using different monitoring methods. The final results are shown in Figure 7.

**Figure 7** Real time monitoring results (a) the real-time performance of the DT-based monitoring method (b) the real-time performance of the GA-based monitoring method (see online version for colours)



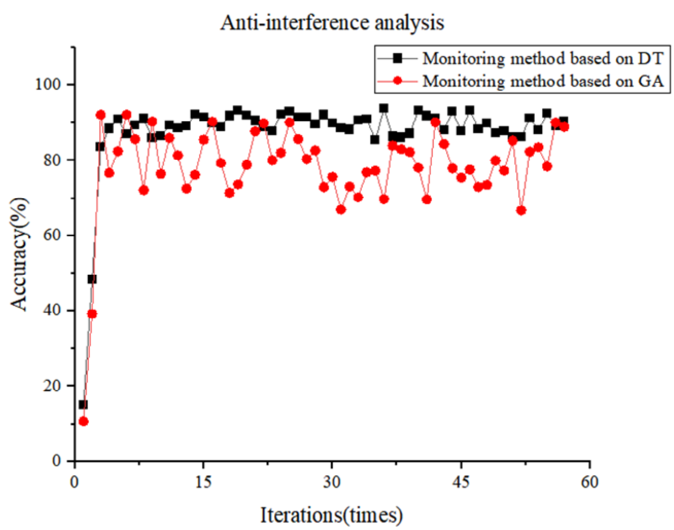

(a) (b)

In Figure 7, the two detection methods exhibit different real-time performance levels under different datasets. In Figure 7(a), the IMS intelligent monitoring method based on DT's average time spent on identifying abnormal states under different datasets was approximately 22.31 seconds, 24.19 seconds, 22.41 seconds, 21.85 seconds, and 23.27 seconds, respectively. The average time spent identifying abnormal states was below 25 seconds. In Figure 7(b), the average time taken by the GA-based IMS variable condition intelligent monitoring method to identify abnormal states in different datasets was approximately 29.67 seconds, 30.90 seconds, 29.23 seconds, 28.16 seconds and 28.89 seconds, respectively. The average time spent identifying abnormal states ranged from 28 seconds to 31 seconds.

### *4.3 Monitoring anti-interference*

The intelligent monitoring process of IMS under variable operating conditions is accompanied by various factors such as noise, interference signals, and environmental changes. Anti-interference monitoring is to evaluate the stability of monitoring methods in the face of various interference factors (Dong et al., 2019). Strong anti-interference ability can effectively filter out noise and interference, ensure the authenticity and effectiveness of information, help improve the accuracy of decision making, and smoothly respond to changes in the environment to maintain the system's normal operation. This article uses a variable operating condition of 2,250 revolutions per minute and a radial force of 11 kN as the monitoring anti-interference testing environment. It adds Gaussian white noise to the testing environment. This article analyses the accuracy changes of monitoring methods to verify the anti-interference ability of intelligent monitoring. The signal-to-noise ratio is measured in 15 decibels (dB), and the final comparison results are shown in Figure 8.

**Figure 8** Monitoring anti-interference results (see online version for colours)




The monitoring anti-interference results in Figure 8 show that compared with the GA-based monitoring method, the IMS variable condition monitoring method under DT technology has stronger stability and anti-interference. Under low iteration times, both monitoring methods show significant improvement in accuracy results in noisy environments. As the number of iterations increases, the accuracy results of the two monitoring methods gradually fall within a specific interval range. From the monitoring accuracy changes of the two types of methods, it can be seen that the IMS variable condition monitoring method based on DT technology in this article has a more stable accuracy change. In contrast, the monitoring method based on GA has a greater trend of accuracy change. From this perspective, the IMS variable condition monitoring method under DT technology can effectively avoid noise interference and maintain more stable and ideal accuracy results.

### 4.4 Fault detection rate

IMS variable condition fault detection is significant for ensuring equipment safety and improving product quality. In the actual operation of IMS, monitoring methods need to monitor faults in the production process promptly. To compare the fault detection rates of the two methods, this article takes ten kinds of bearing fault data randomly selected from different sample datasets as the object. They applied different monitoring methods to monitor the equipment status and conducted 20 repeated experiments to compare the fault detection rate of the monitoring methods. The final results are shown in Figure 9.

**Figure 9** Fault detection rate results, (a) the fault detection rate of the DT-based monitoring method (b) shows the fault detection rate of the GA-based monitoring method (see online version for colours)

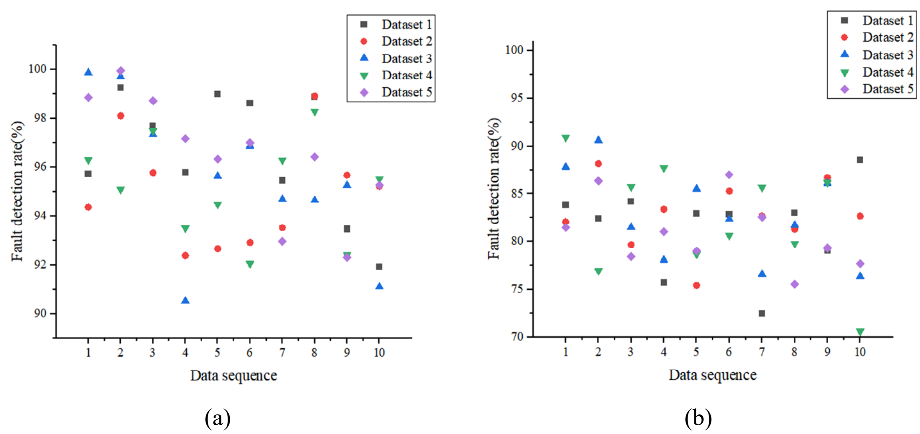



Figure 9 shows a significant difference in the fault detection rate results between the two types of methods. In Figure 9(a), the average fault detection rates of the DT-based monitoring method under different datasets were about 96.57%, 94.95%, 95.56%, 95.14%, and 96.49%, respectively, with the highest average detection rate of 96.57%. In Figure 9(b), the average fault detection rates of the GA-based monitoring method under different datasets were approximately 81.49%, 82.74%, 82.67%, 82.29%, and 80.84%, respectively, with the highest average detection rate of 82.74%. From the comparison results, it can be seen that DT-based monitoring methods have more significant advantages. This result represents that the DT method can more accurately identify and predict faults, and its high detection rate means higher reliability and lower false alarm rate, providing stronger security and stability for IMS.

## 5 Discussion

To verify the effectiveness of DT technology in IMS variable condition intelligent monitoring, this article conducted experimental analysis from four aspects: monitoring accuracy, real-time performance, anti-interference and fault detection rate.

### *5.1 Comparison of monitoring accuracy*

The comparison of monitoring accuracy results shows that the IMS variable condition intelligent monitoring method based on DT shows good monitoring accuracy results in different datasets, and its average monitoring accuracy reaches over 90% in different data samples. Compared with GA-based monitoring methods, IMS variable condition intelligent monitoring under DT can provide more reliable results for analysis. Through high-precision modelling and simulation of smart manufacturing systems, it compares actual operating conditions with virtual models, achieving precise monitoring of operating conditions.

### *5.2 Comparison of real-time monitoring performance*

Compared to the monitoring methods under GA, the intelligent monitoring method based on DT takes more time to identify abnormal states in IMS variable condition monitoring. It can collect and monitor the working condition data of intelligent manufacturing systems, as well as analyse and process multidimensional data to ensure real-time monitoring data.

### *5.3 Comparison of monitoring anti-interference performance*

In the comparison results of monitoring anti-interference, the intelligent monitoring method supported by DT technology has a more stable monitoring accuracy change in noisy environments. Compared with GA-based monitoring methods, intelligent monitoring methods under DT are more conducive to resisting interference factors in IMS variable operating conditions, adapting to changes and interferences in variable operating conditions, and avoiding their impact on monitoring results.

### *5.4 Comparison of fault detection rates*

In the experimental analysis of fault detection rate, the average detection rate of the IMS variable condition intelligent monitoring method based on DT reached 90% under different datasets, which is much higher than the experimental results of the monitoring method based on GA (He and Bai, 2021; Stan et al., 2023). DT technology can continuously monitor and analyse variable operating conditions data, and through fault analysis and simulation, timely detect and prevent faults, providing practical support for IMS operation.

This article uses DT technology to accurately monitor and simulate intelligent manufacturing systems, improving their adaptability to complex working conditions and fault prediction capabilities. Not only can it improve the stability of manufacturing systems to a certain extent, but it can also enhance their reliability, providing new ideas for noise and disturbance problems in complex industrial environments, which is of great significance for promoting the development and application of intelligent manufacturing technology. Compared with genetic algorithms, the method proposed in this paper is more in line with the requirements of intelligent monitoring in modern production processes and has broad application prospects.

## 6 Conclusions

With the development of modern production technology, the application of IMS in actual production and manufacturing is becoming increasingly widespread. The IMS variable condition data scale is large and the environment is complex. Real-time monitoring and analysis of variable condition data is of great significance in ensuring the stable operation of IMS and improving production quality. In order to improve the accuracy of IMS variable condition monitoring and identify and investigate abnormal production conditions, this article combined DT technology to conduct effective research on IMS variable condition intelligent monitoring. This article validates the DT-based IMS full condition intelligent monitoring method from four aspects: monitoring accuracy, real-time performance, anti-interference ability, and fault detection rate. The experimental results show that the intelligent monitoring method based on DT for IMS variable working conditions is superior to the monitoring method based on GA in four dimensions: monitoring accuracy, real-time performance, anti-interference performance, and fault detection rate. Its average monitoring accuracy reaches 93.61%, and the average fault detection rate is 96.57%. It has better comprehensive performance in complex and variable working conditions, providing strong support for the stable operation of intelligent manufacturing systems. This method has higher real-time performance and anti-interference ability than traditional GA. It significantly improves monitoring accuracy and real-time performance and the anti-interference of monitoring methods to a certain extent, achieving reliable and comprehensive fault detection. Although the IMS variable condition intelligent monitoring method based on DT in this article has a specific guiding role in improving production quality and efficiency, there are still limitations in the research process. The intelligent monitoring method for IMS variable working conditions based on DT relies on precise data collection and processing. Any data deviation or loss may affect the accuracy of monitoring results and require high computing resources and professional technical support, which may limit its widespread application in small and medium-sized enterprises. Due to the massive real-time data support necessary for establishing and maintaining the DT model, it poses significant challenges to its computation and storage. The accuracy and reliability of this method heavily depend on the quality and diversity of the samples, which may result in insufficient adaptability to specific working environments. In IMS variable condition monitoring, much real-time data is required to support it. The data selected for experimental analysis in this article is insufficient, and the actual variable condition data has not been analysed. In future research, the quality of data analysis will be continuously improved, thereby promoting the high-quality development of IMS in modern production and manufacturing. In the future, edge computing, 5G and other emerging technologies can be combined to achieve more real-time and cost-effective intelligent monitoring solutions. Through these improvements, DT technology will unleash greater potential in intelligent manufacturing. Further development of more effective data processing and analysis methods can reduce the demand for data quantity and quality, and by optimising the modelling process and technical architecture, DT's construction and maintenance costs.

## Declarations

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All authors declare that they have no conflicts of interest.

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