Digital Twin-Based Production Workshop Efficiency Optimization

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Abstract. As the main battlefield of the new generation of intelligent manufacturing, it is crucial to explore potential problems and optimize production efficiency of the production workshop. In this paper, we propose a dynamic and iterative method to optimize the efficiency of the production workshop by taking the Overall Efficiency of Equipment (OEE) as evaluation index. Firstly, we summarize the six major time losses affecting OEE into equipment abnormal state and human loss, which can be monitored and recorded in real time. Then, we construct an optimization platform that can update OEE in real time based on digital twin. Finally, taking monitoring the start-up operating temperature of an equipment as an example, the operation process and method library update of the platform are explained, and the iterative improvement of equipment production efficiency is realized. This study has reference significance for promoting the intelligent upgrading of the production workshop.

Keywords: Digital twin · OEE · Production workshop · Support vector regression

1 Introduction

With the introduction of policies such as "Industry 4.0", "Industrial Internet " and "Made in China 2025", the wave of the fourth industrial revolution has swept the entire manufacturing industry. How to achieve long-term and stable development in the fierce market competition has become an urgent challenge for manufacturing enterprises. Among them, the workshop equipment is a main factor to affect the productivity of enterprises.

Equipment management is the act of managing the lifecycle of equipment [1]. The equipment lifecycle management includes five aspects: design, manufacture, use, maintenance and scrapping [2]. At present, with the development of new generation information technology such as big data, cloud computing, artificial intelligence and other information technologies, the equipment management is developing in the direction of digitalization, networking and intelligence.

Since digital twin (DT) has the characteristics of virtual-real integration, and continuous iterative optimization [3], which have been widely applied to the equipment lifecycle

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management. Therefore, scholars have conducted in-depth research on equipment management based on DT technology. Fei Tao et al. (2019) [4] proposed a prognostics and health management (PHM) model for services such as device assessment, fault diagnosis and life prediction based on DT. Ruirui Wang et al. (2022) [5] built an industrial internet platform for marine gas turbine health management that enables real-time interaction and dynamic update of management data and model information. In order to deal with the reliability assurance issues of complex power grid systems, Zongmin Jiang et al. (2021) [6] proposed an OKDD (ontology-body, knowledge-body, data-body and digital-portal) digital twin body model which is conducive to the hierarchical creation for complex systems proved by the developed prognostic and health management (PHM) system demo in a 110 kV substation simply. To optimize the scheduling activity, Elisa Negr et al. (2021) [7] proposed a proof-of-concept of a simheuristics framework composed of genetic algorithms and DT-based Equipment PHM module for robust scheduling applied to a Flow Shop Scheduling Problem whose viability was demonstrated in a laboratory environment. Wihan Booyse et al. (2020) [8] proposed a Deep Digital Twin framework which is able to detect incipient faults, track asset degradation and differentiate between failure modes in both stationary and non-stationary operating conditions when trained on only healthy operating data. Through the finite element analysis of DT model, Qing-Wei Li et al. (2020) [9] evaluated the current safety status of FAST cable-net and predicted the fatigue life of components in the cable-net so as to realize the Condition-Based Maintenance (CBM) of FAST cable-net structure.

Applying DT to PHM can go a long way towards improving equipment productivity, reducing equipment breakdowns and extending equipment life. But workshop productivity is not only linked to the health of the equipment condition, but also closely related to the environment, personnel and other factors. The root causes behind the six time losses that define OEE are tightly linked to the equipment, people and environment in the workshop. In the following paper, we will build a workshop equipment efficiency optimization platform based on DT and propose a method library including various methods for solving different causes of losses, while the method library can be updated and iterated as the production process progresses based on that platform. Then we will use the start-up operation temperature of a piece of equipment as an example to explain the operation process of this workshop efficiency optimization platform and the update of the method library.

2 Construction of Equipment Efficiency Optimization Platform

2.1 Analysis of Six Major Losses

The six major time losses include: downtime losses due to production preparation and adjustment, downtime losses due to equipment failure, idle and short downtime losses, processing speed reduction losses, product quality defects such as rework and scrap, and yield losses due to trial production [10]. OEE, an important part of Total Productive Maintenance (TPM), is an important indicator of equipment productivity and is calculated precisely by the six time losses defined as shown in Eqs. (1) to (4) [11].

$$\mathrm{OEE} = \mathrm{V} * \mathrm{P} * \mathrm{Q} \tag{1}$$

$$V = \frac{\text{loading time - downtime}}{\text{loading time}} \tag{2}$$

$$P = \frac{\text{theoretical cycle time} \ * \ \text{processed amount}}{\text{operating time}} \tag{3}$$

$$Q = \frac{\text{processed amount - defect amount}}{\text{processed amount}} \tag{4}$$

Loading time: Actual working time minus planned downtime.
Downtime: the stoppage time loss due to breakdowns, setup and adjustments.
Theoretical cycle time: Theoretical production time per unit of product.
Operating time: Actual working time in a production cycle.
Processed amount: Actual output in a production cycle.
Defect amount: Defective product within a production cycle.

The advantage of OEE is that it can accurately calculate the production efficiency of the equipment, while its disadvantage is that only calculate the productivity of a machine within a certain production cycle. OEE is a static indicator of equipment productivity. This paper analyses the six major time losses affecting OEE, which are summarised as unavoidable losses, human losses and abnormal equipment condition losses, as shown in Fig. 1. Based on digital twin, the virtual workshop can process and analyse real-time loss data from the physical workshop, providing the basis for real-time dynamic updates of OEE and iterative optimization of workshop equipment efficiency.

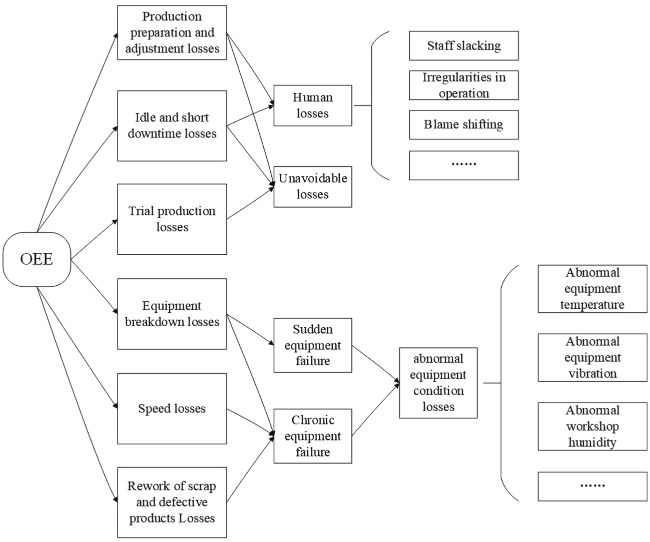

Fig. 1. Analysis and induction of OEE

2.2 Framework of the Workshop Equipment Efficiency Optimization Platform

The construction of a workshop equipment efficiency optimization platform framework requires the collection, processing, storage, calculation, analysis and application of workshop operation data. Therefore, this paper proposes four layers for constructing the framework of workshop equipment efficiency optimization platform based on the five-dimensional model of DT proposed based on Fei Tao et al. [4], which are physical perception layer, connection and communication layer, analysis and calculation layer and decision application layer, The framework is shown in Fig. 2.

(1) Physical perception layer:

This layer can use intelligent sensing technology to achieve real-time recording of equipment and personnel data in the physical workshop. For example, through external sensors, the workshop working condition data can be sensed and recorded in real time. Video monitoring and equipment sensors enable real-time sensing of employee work positions and operations respectively.

(2) Connection and communication layer

This layer can use the Internet of Things, human-computer interaction, edge cloud collaboration and big data analysis technologies to process, store and manage the data obtained from the intelligent sensing layer in real time, thus providing the data basis for the analysis and calculation layer to build a virtual workshop and identify problems. This layer also provides feedback to the physical workshop from the analysis and computing layer, enabling the control of equipment and personnel in the physical workshop.

(3) Analytical computing layer

This layer uses the data obtained from the connection communication layer to build a virtual workshop. This virtual workshop can use machine learning, neural network algorithms and knowledge to build a library of models for real-time monitoring and evaluation of workshop equipment and staff. For example, if the equipment operating temperature model detects an abnormal equipment operating temperature resulting in the OEE below the benchmark, the workshop production status can be considered abnormal.

(4) Decision-making application layer

This layer uses the abnormal workshop status data identified from the analysis and calculation layer to generate textual information describing the abnormalities in the shop floor. The workshop manager can suggest solutions based on this textual information, thus creating a library of solutions. If another device has a previously resolved exception, the corresponding method in the method library can be called directly to resolve it.

2.3 Design of Equipment Efficiency Optimization Platform

The flow of the DT-based equipment efficiency optimization platform is shown in Fig. 3. When the physical workshop starts its production activities, the operating conditions of the equipment and employee operations are recorded by the corresponding sensors in

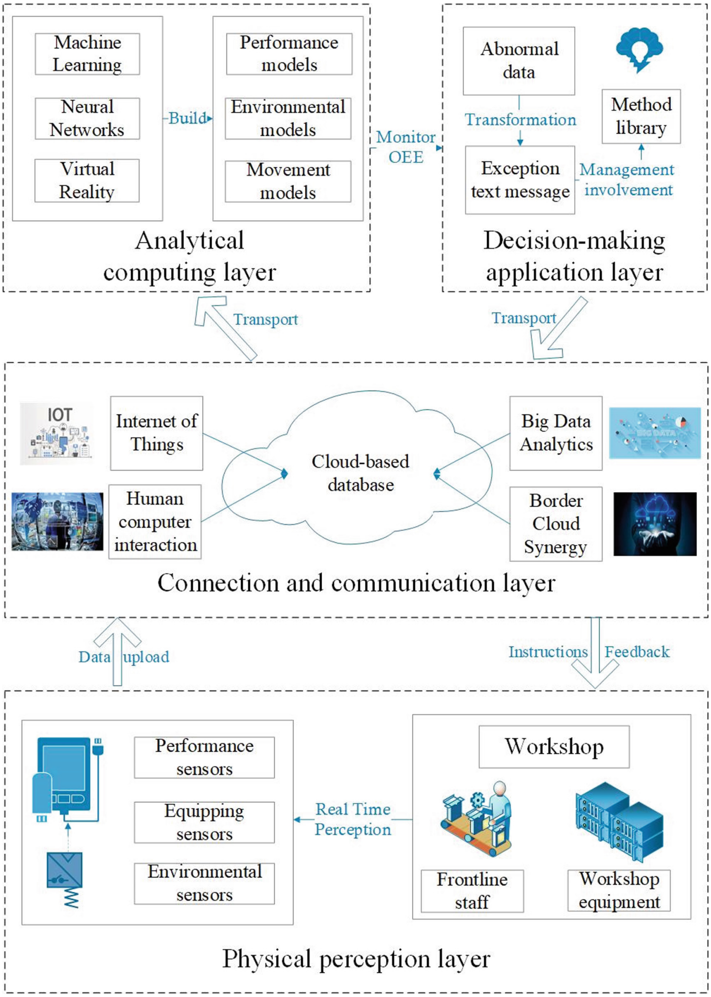

Fig. 2. Framework of the workshop equipment efficiency optimization platform

real time and transmitted to the virtual workshop as a data stream. The virtual workshop stores, processes and analyses the data streams from different sources, and invokes appropriate algorithms to build models for real-time monitoring of the production equipment and frontline employees in the workshop. If the real-time operating data of a production process in the workshop is outside the normal prediction range of the monitoring model, the real-time OEE of the equipment is lower than the set benchmark. The management staff then proposes a solution to the production anomaly that has caused the OEE to drop and stores it in the method library. This method is then applied by the management staff to improve the OEE and hence the productivity of the equipment. As the process iterates between the physical and virtual workshop, the OEE bottleneck is breached

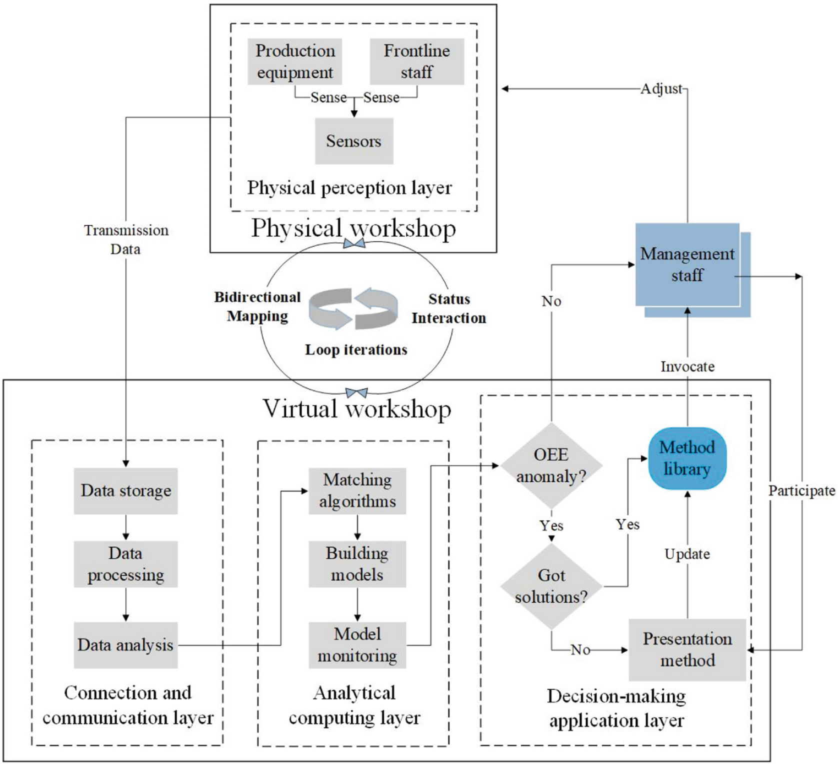

Fig. 3. Digital twin-based equipment efficiency optimisation platform

until it is infinitely close to the productivity of the workshop, which is only affected by unavoidable losses.

3 A Case Study

This paper analyses the operation of the DT-based workshop equipment efficiency optimization platform constructed above, using the monitoring of the start-up operating temperature of a production plant as an example.

3.1 Construction and Evaluation of Model

It is assumed that the production equipment has a start-up time of 90 s. The virtual workshop visualises and analyses this period of data transmitted from the temperature sensor. The time-temperature relationship for this equipment is shown in Fig. 4. As can be seen from the figure, the start-up temperature monitoring model for this equipment can be constructed in this paper using the support vector regression (SVR) for time series analysis.

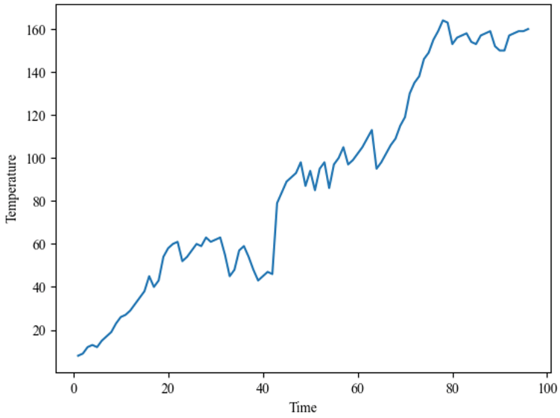

Fig. 4. Time-temperature curve

The virtual workshop divided 25% of this temperature data set into a test set and 75% into a training set, and the model was trained and the parameters were optimized by grid search method (GS) and 5-fold cross-validation, finally the model was trained with penalty parameter c = 400 and rbf kernel function parameter g = 0.00125, the fitting results of the model predicted and actual values are shown in Fig. 5. From the figure, it can be seen that the predicted and actual values, with a good fit of $R^2 = 95.27\%$, and the model training is superior. The GS-SVR model is therefore excellent at simulating and predicting changes in the start-up temperature of this type of equipment and monitoring it in real time).

3.2 Creation and Updating of Method Library

As the equipment continues to operate, the model monitors the temperature of the equipment. When the start-up temperature of the equipment is outside the normal range monitored by the model and the real-time OEE of the equipment falls into the benchmark, managers need to propose a solution to the equipment temperature anomaly. For example, when equipment temperatures are too high, short shutdowns, physical cooling and reduced production power can be implemented. Therefore, when other equipment has a temperature anomaly that causes a drop in OEE, the management staff of the workshop can directly call on the method library to resolve such production anomalies. When an abnormal workshop production condition is resolved, the virtual workshop method library is updated and expanded once, while a certain bottleneck in equipment productivity is reached. As workshop production iterates through the cycle, the method library is updated and the bottleneck in equipment productivity is breached until the library contains methods to address all equipment abnormal state losses and human losses, except for unavoidable losses.

Some of the solutions for human losses and abnormal equipment condition losses are summarised in Table 1.

The equipment efficiency optimization platform combining OEE with DT not only gives the static indicator OEE the ability to dynamically monitor equipment productivity

Table 1. Partial settlement of human losses and abnormal equipment condition losses

human losses		abnormal equipment condition losses	
problem	measures	problem	measures
Staff slacking	Parallel rewards and sanctions Open feedback channels Provide recreational activities	Abnormal equipment temperature	Temporary shutdown physical cooling reduced production power
Irregularities in operation	Regular training and assessment	Abnormal workshop humidity	Moisture absorption ventilation
Blame shifting	Role de-blurring	Abnormal equipment vibration	Replacing ageing circuits Replacing worn parts

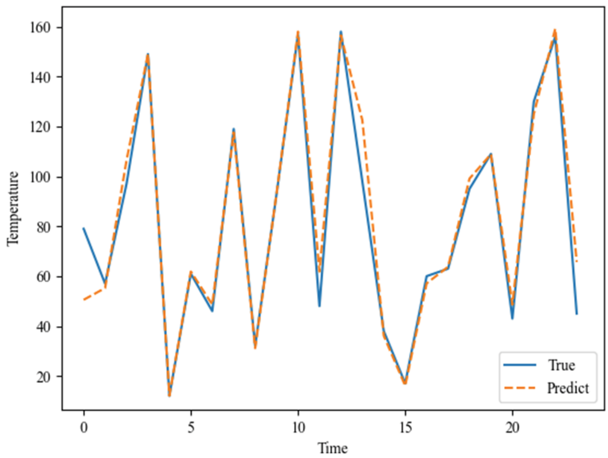

Fig. 5. Fitted comparison of predicted and actual equipment temperature values

in real time, but also incorporates factors other than equipment such as people and environment into the "digital twin + PHM model". This will provide a reference for future research on intelligent operations and maintenance management throughout the equipment life cycle.

4 Conclusion

In this paper, a DT-based workshop equipment efficiency optimization platform is constructed with the goal of optimizing workshop productivity. The platform then finds suitable algorithms to build predictive models for dynamic monitoring of OEE based on the data characteristics of different human losses and equipment abnormal state losses. Finally, this paper proposes qualitative and quantitative methods to build a library of methods for different causes of losses so as to achieve iterative optimization of production workshop efficiency.

However, this paper is still lacking in the construction of intelligent models and the methods in the method library are too empirical. Future study needs to continue in the direction of applying intelligent algorithms to propose solutions.

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