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Research Article

Thermal Power Plant Turbine Rotor Digital Twin Automation Construction and Monitoring System

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Based on the digital twin technology, this article investigates the physical rules fusion model of the turbine rotor operation in thermal power plants, establishes the geometric behavior mapping method of the turbine rotor in the virtual scenario of thermal power plants, and develops a real-time data-driven virtual monitoring system of the rotor operation, which realizes the virtual control of the rotor operation process from the physical and geometric levels, respectively. The 3D model created by Creo was imported into ADAMS in *x_t* format, constraints were added, and model data input and output interfaces were established in ADAMS software to build its dynamics model. The foundation of the joint simulation with the AMESim model is laid. The information fusion technology based on *D-S* evidence theory, fusing multisensor data and information from other channels, can more accurately and comprehensively understand and describe the diagnostic object, to make correct judgment and decisions on complex fault diagnosis. We propose an integrated modeling method for multiview control scenarios of manufacturing units based on digital twins and finalize the construction of digital twin models of manufacturing units based on the definition of the multiview model collaboration mechanism, which provides model support for the research of digital twin-driven manufacturing unit control technology. For the twin data perception and interaction problem, a unified architecture-standardized communication protocol is established based on OPC UA technology to solve the problem of difficult data perception and interaction caused by the nonuniform communication interface protocol of different devices on the automated production line. The model change is intended to help improve the visualization level of digital production line monitoring and improve the operating efficiency of the turbine rotor. The experimental results show that the application of digital twin to thermal turbine rotor operation monitoring provides a new method for turbine rotor vibration fault diagnosis; *D-S* evidence theory can fuse information from multiple aspects of the fault, thus improving the probability of fault diagnosis and reducing uncertainty.

1. Introduction

With the rapid development of the economy and society and the further acceleration of the industrialization process, the electricity demand is more, the power industry has seen unprecedented development, and high parameters and large-capacity generating sets continue to build and put into operation one after another, while the structure and system of the equipment are becoming increasingly complex. Equipment work intensity is increasing production efficiency, automation is getting higher and higher, and at the same time, the equipment is more complex, the association of various parts increasingly closely, often a small failure somewhere on the outbreak of chain reaction, resulting in the entire equipment and even its related equipment environment of catastrophic damage. All these accidents cause huge economic and environmental losses and even casualties [1]. Therefore, how to ensure the safe and reliable operation of the unit is of great importance to the development of the national economy. In the power plant, the turbine is one of the three main engines, but also an important large rotating machinery, is a machine, electricity, and liquid coupled together in a complex system, is responsible for the conversion of thermal energy into mechanical energy and then into electrical energy key equipment, in the high speed, high stress, high temperature working environment, the components are subject to large loads, and often subject to a variety of alternating stress. Due to the complexity of the equipment structure and the special characteristics of the operating environment, the failure rate of turbine generator sets is high and the danger of failure is also high. The failure of turbine generator sets accounts for a considerable proportion of power plant failures, and once they occur, they will cause huge economic losses and serious social impacts to the enterprise and the country [2]. The problem of turbine fault prediction and diagnosis has always been highly valued by relevant research institutions, enterprises, and management departments, and is an important aspect of the application of modern fault diagnosis technology, in which the turbine rotor becomes an important aspect of turbine fault prediction and diagnosis due to its importance in the turbine generator set and the special nature of the working environment. As each part of the equipment becomes increasingly closely related, often a small fault somewhere will cause a chain reaction, resulting in catastrophic damage to the entire equipment and even its related equipment environment.

The use of digital technology helps to monitor faults, and the method of condition monitoring and prediction by building a simulation model highly like the operating entity is still in its infancy. In this regard, a multidomain digital model of the regulating oil engine can be built for application in the study of regulating oil engine faults. This improves the two ways of artificially injecting faults and destroying parts to collect data in the future, as well as the problem that some fault data are difficult to obtain. With the remarkable improvement of information technology, increased devices are also equipped with sensors and communication capabilities. Big data analysis in the information space enables computational intelligence [3]. And advances in sensor and communication technologies provide the basis for connecting the physical world of machines and equipment with the information world of computers. New ways of assembling and integrating information-physical systems like this into manufacturing have led to a new focus on digital twin technology. We have conducted a lot of research and practice in emerging technologies such as Big Data, The Internet of Things (IoT), Cloud Computing, Artificial Intelligence, and Blockchain. As an enabling technology and means to practice the concept of smart manufacturing, digital twin technology can effectively solve the problem of information-physical fusion in smart manufacturing, and it has been paid more attention by scholars to study and use to solve practical engineering problems. At present, in the field of industrial process monitoring, the use of data in the manufacturing process is mostly focused on production management and control in the form of intuitive visualization, as well as historical data for traceability, but it is not used to realize the mapping and interactive integration of physical space and information space. The demand for real-time display and online monitoring of equipment operation status, product production quality, and other related status monitoring data in the manufacturing process is becoming increasingly urgent [4]. Digital twin technology can accurately simulate and portray the behavior of physical entities in the real world, and the establishment of digital twin models of automated production line manufacturing process can make the manufacturing process more "digital" and "transparent," which is essential for enterprise production process optimization, cost reduction and efficiency improvement, and quality improvement. The establishment of a digital twin model of the manufacturing process of the automated production line can make the manufacturing process more "digital" and "transparent," which is of great practical significance for the optimization of the production process, cost reduction, and efficiency increase, and quality improvement of enterprises.

As an enabling technology and means to practice the concept of smart manufacturing, digital twin technology can effectively solve the problem of information-physical integration of smart manufacturing and has become a hot spot of attention in academia and industry worldwide. At present, in the field of industrial process monitoring, the use of data in the manufacturing process is mostly focused on intuitive visualization for production management and control, as well as historical data for traceability, but it is not used to realize the mapping and interactive integration of physical space and information space [5]. The demand for real-time display and online monitoring of equipment operation status, product production quality, and other related status monitoring data in the manufacturing process is becoming increasingly urgent. Digital twin technology can accurately simulate and portray the behavior of physical entities in the real world. The establishment of digital twin models of automated production line manufacturing process can characterize and map the manufacturing process in real-time, which is of great practical significance for enterprise production process optimization, cost reduction and efficiency increase, and quality improvement [6]. Therefore, based on digital twin technology, this article will build a digital twin model of the equipment from the perspective of production line equipment by building a physical rule fusion model of the equipment and establishing a geometric behavior mapping method of the equipment in the virtual scene to realize the virtual monitoring of the production line operation process from the physical level and geometric level, respectively. It will help to improve the monitoring and management level of the digital production line, then improve the production efficiency of enterprises and accelerate the transformation and upgrading rate of China's manufacturing industry.

2. Related Works

It is widely believed that the concept of the digital twin was first introduced by Professor Michael Grieves of the University of Michigan, USA, who proposed the concept of "virtual digital representation with physical product equivalence" for Product Lifecycle Management (PLM) in a slide presentation to the industry at the inception of the PLM Center in 2002. The concept of "virtual digital representation with physical product equivalence" was introduced in his presentation to the industry at the inception of the PLM Center in 2002 [7]. In related research, NASA has pioneered the introduction of digital twin technology in the health maintenance and assurance of aerospace vehicles to analyze and evaluate the condition performance of the vehicle and to predict whether the load will be able to complete the next mission. Takizawa et al. analyzed the concept of the digital twin, applied digital twin technology to the monitoring of production processes, outlined a multifunctional production process approach, and finally proposed a digital twin-based manufacturing process monitoring algorithm [8]. To address the problem of the interconnection of complex discrete manufacturing systems, a modeling method is designed to quickly create a virtual model and a data interaction mechanism between the production system in the physical world of the workshop and its mirror virtual model, and finally, a digital twin model of a complex discrete manufacturing workshop is built. As the level of mechanical manufacturing continues to improve, the manufacturing process of process products becomes more complex, and possible abnormalities in the production process will occur more frequently [9]. The traditional production process monitoring method based on manual records, two-dimensional reports, and configuration monitoring is no longer sufficient for the increasingly advanced and complex manufacturing processes. To improve the visualization and transparency of the manufacturing process, many scholars have conducted research related to the visualization and monitoring of the production process. Wang et al. developed a Web-based 3D visualization and real-time monitoring system of the dam material transportation process based on 3dsMax and ActiveX technologies, which realized the visual representation of the vehicles and the surrounding environment, and the system is networked, digitalized, and visualized [10]. Tao et al. realized the 3D visualization inspection of the tunnel based on OpenGL and VB technology and visually represented the inspection data, which made the inspection results more intuitive and clearer [11]. Thiruvasagam et al. developed a remote monitoring system with 3D virtual reality technology based on B/S architecture, using VRML and Java language, which provides a technical guarantee and implementation solution for the application of 3D virtual monitoring technology in the industry [12].

The development of fault diagnosis technology has become an independent and interdisciplinary comprehensive information processing technology today. The integration of equipment fault diagnosis technology and current frontier science is the development direction of equipment fault diagnosis technology. The development trend of diagnosis technology is the precision and multidimensionality of sensors and the diversification of diagnosis theory and diagnosis model [13]. Since the turbine unit is working under the special environmental conditions of high temperature, high pressure, high speed, and high stress, the performance of the sensor is very demanding in the turbine unit fault diagnosis system. At present, the research on sensors is mainly focused on improving the reliability of sensor performance, developing new sensors, and studying how to fuse sensor faults to reduce the misdiagnosis rate and leakage rate. Currently, many scholars are studying the use of multisensor information fusion technology to diagnose faults and improve the resolution and accuracy of faults. Currently, the research methods for turbine unit fault mechanisms include the field test method, laboratory simulation method, and computer simulation method. The laboratory simulation research method is to first establish a physical model of the unit, i.e., a simulation test bench, and then artificially preset the fault of the unit on the simulation test bench, detect the fault signal under the preset fault state, extract the fault characteristics, and then establish the mapping relationship between the fault signs and the fault. This method overcomes the shortcomings of the field experiment method and is a widely adopted fault study method [14]. However, the fidelity of the fault state of this method is reduced and the range of simulated faults is limited. Gray analysis, time series analysis, cepstrum analysis, holographic spectrum analysis, artificial intelligence expert system for fault diagnosis, and artificial neural network system have been applied to mechanical equipment fault diagnosis in large numbers, and many techniques have become mature. In the field of turbine fault diagnosis, the commonly used diagnostic strategies are comparative diagnosis, logical diagnosis, statistical diagnosis, pattern recognition, diagnosis based on gray theory, fuzzy diagnosis, expert systems, and diagnosis based on artificial neural networks. Bailey established a Bayesian network model, which is mainly used to deal with the damage mechanism of the dynamic blades of turbines and the interaction of failure modes [15]. The experimental results showed that the cracks were closed in the case of the compression part expansion rate of the fatigue cycle. Xie et al. predicted the local strain life of the turbine's final stage at low flow conditions based on the elastic-plastic analysis. The three-dimensional transient flow field, strain distribution, and stress distribution of the final stage blade were calculated using a two-way fluid-structure coupling method considering the nonconstant flow steam force and the local high temperature of the blade [16].

3. Construction of an Automated Monitoring Model for Turbine Rotors in Thermal Power Plants Based on Digital Twins

3.1. Digital Twin Model Design. Under the trend of intelligent and informative development, the application of big data, the Internet of Things, and intelligent algorithms, based on digital twin technology can realize the interconnection and interactive mapping of transformer physical space and digital space, and establish a full-factor, hyper-realistic transformer digital twin in virtual space to simulate the operation state of physical entities in real-time for online monitoring. Digital twin technology can accurately simulate and portray the behavior of physical entities in the real world. Digital twin technology can make the manufacturing process more "digital" and "transparent," which has important practical significance for enterprise production process optimization, cost reduction and efficiency improvement, and quality improvement, and plays a substantial role in promoting traditional manufacturing to intelligent manufacturing. The establishment of a digital twin model for the manufacturing process of automated production lines can make the manufacturing process more “digital” and “transparent,” which is of great practical significance for enterprises to improve quality, control risks, and reduce costs. To realize the digital twin of the manufacturing process of the automated production line, this chapter focuses on the analysis of the digital twin system architecture of the relevant manufacturing workshops and establishes the architecture of the digital twin system for the manufacturing process of the automated production line based on the existing digital twin technology theory. At the same time, a test platform for monitoring the status of the manufacturing process of the automated production line was built. The automated production line is a complex and complete mechatronic device system with comprehensive and systematic characteristics, which integrates multiple technologies [17]. In this article, based on the existing research on the digital twin workshop system, the concept of a digital twin five-dimensional model is proposed concerning the previous results, and the architecture of the digital twin system for the manufacturing process of the automated production line is proposed. The digital twin technology-based turbine rotor automation monitoring model for thermal power plants is shown in Figure 1. The architecture mainly consists of four parts: physical entity layer, virtual model layer, twin data layer, and application service layer, and the information interaction is realized through the connection between each layer.

The digital twin model interaction mode describes the flow of physical data between the physical entity of the rotor, the digital twin, the data center, and the rotor fault diagnosis system. Real-time physical data is extracted from the rotor physical entity, including state-aware information and gas-in-oil data, where the state-aware information is used to dynamically update the rotor digital twin in real-time to bring it closer to the physical entity; the gas-in-oil data is used to diagnose rotor faults and to know the rotor fault conditions, enabling the real-time simulation of rotor operation [18]. The data center houses the rotor lifecycle data, the physical entity real-time data, the digital twin simulation data, the gas in oil data, and the data derived from the computational iterations. Through the analysis of the gas in oil and input to the fault diagnosis model of the digital twin, the fault diagnosis results are output and uploaded to the diagnostic system, and the fault results and maintenance solutions are provided to the engineers for reference.

The three ontology description languages recommended by the World Wide Web Consortium (W3C) are RDF, RDFS, and OWL, in which RDF is a resource description framework to describe the resource information on the web and the relationship between them. OWL can describe the ontology semantically. The advantage of OWL is that it not only maintains the compatibility of RDF and RDFS but also has stronger semantic expression and more powerful reasoning and logical description ability, compared with RDF and RDFS, OWL can describe the knowledge more fully. Therefore, this article adopts OWL as the transformer ontology modeling description language to build the transformer ontology model.

$$c = \begin{cases} c_1, & p(c_1, x_1), \\ c_2, & p(c_2, x_2), \\ 0, & \text{otherwise}, \end{cases} \qquad (1)$$
$$h(t+1) = F\big(x_{ij}(t)\big) + \big(x_i - x_j(t)\big).$$

The variation factor F determines the convergence and diversity of the population and takes a value between [0,2]. When the value of F is small, the degree of variation between populations becomes smaller, and the evolutionary process of the population becomes inconsistent, causing the population to converge prematurely. When F is large, the search process can easily jump out of the local extremes, but the convergence speed will become slower.

$$F = \frac{(F_{\max} - F_{\min})}{(T - t)}, \qquad (2)$$

where t is the current algebra, T is the maximum algebra, $F_{\max}$ and $F_{\min}$ are the maximum and minimum values. In the early stage of the search, the value of F is larger, which is more favorable to expand the search space of the operation and maintain the diversity of the population; in the late stage of the search, the value of F is smaller, which is more favorable to the algorithm to search in the optimal region and thus improve the accuracy and convergence speed.

The digital twin model needs to be highly modular, well scalable, and dynamically adaptable, and the construction of the model can be done in the information space using parametric modeling methods. Virtual models of physical entities are built-in software such as Tecnomatrix, Demo3D, and Visual Components. The virtual models contain a complete dynamic engineering information description of each physical object, in addition to a description of the geometric information and topological relationships of the automated production line. Then, multiple dimensional attributes of the model are parametrically defined to achieve real-time mapping of the manufacturing process of the automated production line [19]. Virtual-real mapping is to objectively describe the real physical space hydraulic system with ontology and semantic network and construct its knowledge map, which can clearly show the relative position, connection relationship, and semantic structure of each component of the real hydraulic system, to perform full-element mapping (including semantic matching and semantic mapping) to form a digital twin of the virtual space hydraulic system composed of geometric, rule, structural, and behavioral models. Based on the establishment of the physical space entity model and information space twin model, the virtual-real mapping association between them is further established, and the formal modeling language is used to model the virtual-real mapping association relationship.

$$\begin{cases} PS = PE \times PP \times PW, \\ CS = DE \times DP \times DW, \\ PS \leftrightarrow CS, \end{cases} \qquad (3)$$

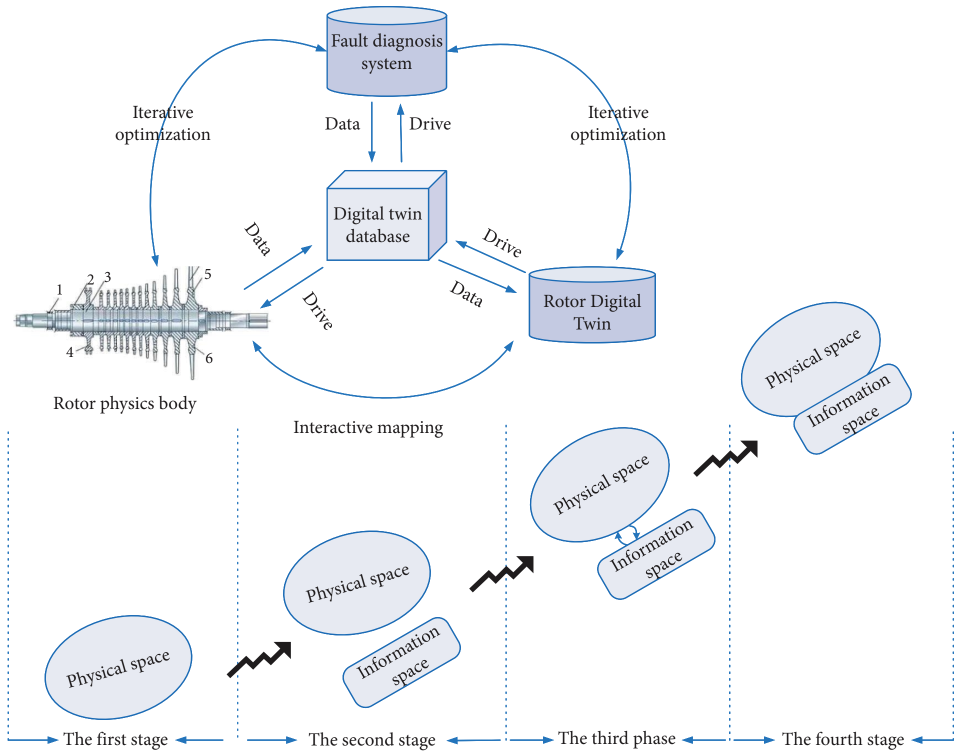

Figure 1: Digital twin model interaction pattern.

where ↔ denotes the bidirectional real mapping between the physical space entity model and the information space twin model and × denotes the natural connection between different models. From this, it can be derived that entity devices and twin devices, entity products, and twin products, and entity personnel and twin personnel should all keep synchronized with each other in a bidirectional real mapping.

3.2. Thermal Power Plant Turbine Rotor Automation Monitoring Model Construction. The experiment was conducted to simulate four common faults of turbine rotors, namely, unbalance, misalignment, friction, and bearing loosening faults. The experiments were performed on the same test bench at different times using the Bently standard test bench, which has easy adjustment means. First, the drive motor shaft is aligned with the experimental shaft, the connection nuts are tightened, and then the balance is found so that the system is in the initial state. Since the experiments are performed sequentially, the initial state for each fault is the simulated state before the elimination of the various faults, including the operation of "aligning the drive motor shaft with the experimental shaft, tightening the connecting nuts, and returning the system to the balanced state." The sampling frequency is 2000 Hz, the filtering frequency is 1000 Hz, and the sampling points are 20 k. A total of 10 groups of unbalanced experiments were made, 7 groups of friction faults were made, 4 groups of misalignment faults were made, and 5 groups of bearing loosening faults were made. In other words, 4 to 10 sets of tests were made for each fault, and each set of the fault data file contains data of 5 channels. Through the interconnection and interactive mapping between the physical space and the digital space of the digital twin technology, a full-element, hyper-realistic digital twin of the transformer is established in the virtual space to simulate the running state of the physical entity in real-time, to achieve the purpose of online monitoring.

In the rotor vibration test bench preset fault settings, the rotor rotation when the transverse displacement of the rotor shaft, after the displacement sensor will be displacement signal into electrical signals, and then after the power supply and signal bias, into the filter for filtering, by the high-speed synchronous sampling board for sampling, to get the required data files [20]. The hardware of the experimental system mainly includes an analog rotor test bench, eddy current sensor, signal pre-processing board, A/D board, and computer. The rotor vibration signal is sampled by the sensor and sent to the signal pre-processing board for filtering and straightening, and the pre-processed vibration signal is converted from analog signal to digital signal by the A/D board and analyzed and processed by the computer. The rotor is driven by the motor and its speed control device to rotate at a certain speed, and the sensor probes in three positions are mounted on the probe mounting bracket at the corresponding measurement points. Probes in x-direction and y-direction are available at measurement point 1 and measurement point 2. The signals are input to the computer through a pre-processing board and A/D digital-to-analog conversion.

$$X(j\varpi) = \sum_{n=0} x_j(\varpi)^n. \quad (4)$$

With different observation perspectives, the signal analysis domain is also different, and a signal can be analyzed from time domain analysis, frequency domain analysis, or both time and frequency perspectives. The time domain analysis of a signal refers to the analysis of the signal performance in the time domain (i.e., waveform), such as amplitude analysis (including the analysis of parameters such as the maximum value, minimum value, and mean value of the signal) and correlation analysis (refers to the analysis of the degree of self-similarity or mutual similarity of the signal at a certain moment). Similarly, the frequency domain analysis of the signal is the analysis of the signal in the frequency domain (i.e., spectrum, which reflects the energy distribution of the signal), such as amplitude spectrum analysis, phase spectrum analysis, power spectrum analysis, and various density spectrum analysis. The time-frequency domain analysis of the signal can be analyzed in both the time domain and frequency domain, such as wavelet analysis. The different expressions of the signal in the frequency and time domains reflect two different aspects of the signal [21]. Observing the signal in the time domain is more emotional and easier to understand while observing the signal in the frequency domain is more rational and difficult to understand, but often leads to deeper and more essential things. As shown in Figure 2, shows the situation of observing a continuous-time signal from the perspective of the time domain and frequency domain, respectively.

When the sampling rate of $x(t)$ reaches twice the highest spectral component contained in $x(t)$, the spectrum of the sampled signal can be completely separated, so that only the data within one cycle in its frequency domain are retained to reconstruct the original time domain signal without distortion. From the theory of the continuous-time system, it is known that the frequency of continuous, periodic time function is discrete and nonperiodic, the spectrum of continuous, nonperiodic time function is continuous and nonperiodic, and the spectrum of discrete, nonperiodic time function is continuous and periodic, the discrete and periodic nature of the signal shows a strong symmetry in the time and frequency domain signals. It is inferred that when the signal is the discrete and periodic form in the time domain, its corresponding frequency domain form must be periodic and discrete. This gives a digital implementation of the Fourier integral (transform), the discrete Fourier transform (DFT). The digital twin model interaction model describes the flow of physical data between the rotor physical entity, the digital twin, the data center, and the rotor fault diagnosis system.

Based on the structural characteristics of the actual turbine rotor, a three-dimensional model of the rotor was created using the software. Since the 3D modeling is closer to the actual operation results, ANSYS was used to analyze the 3D model of the rotor. In the 3D modeling process, the rotor part was reasonably simplified to save some calculation costs, provided that the accuracy of the results was guaranteed. The 3D model was analyzed using ANSYS, and the temperature distribution and stress distribution of the 3D model were calculated. The reading time density was adjusted to 60 S, i.e., 1-minute interval, so that a total of 600 minutes of analysis time was available, making it easier to analyze the turbine rotor material of 30Cr1Mo1V steel. The rotor model in this article does not have a central hole, and the stresses in the rotor without a central hole are mainly concentrated on the rotor surface [22]. During the whole starting process, the stress at the center of the rotor is less than the stress at the rotor surface. The maximum stress trend of the rotor is that the stress increases with temperature. After starting and reaching 3000 r/min, the temperature does not increase and the stress decreases as the temperature is maintained. When ANSYS was used to analyze the rotor start-up process, it was found that the stresses in the rotor were mainly concentrated at the regulating stage, the front slot of the regulating stage, and the blade root, and each point was named A, B, C, and D. A, B, C, and D were marked as monitoring points and should be paid attention to during the whole start-up process. If the stress at these four points does not exceed the maximum stress that the material can withstand, the stress in other parts is also safe. The stress change curve of the turbine rotor in the thermal power plant is shown in Figure 3.

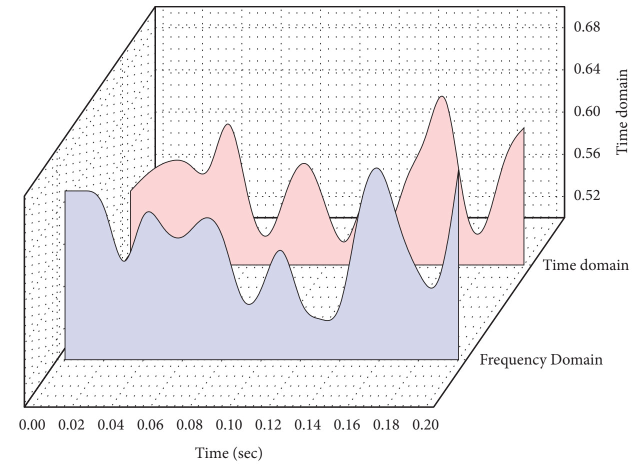

Figure 2: Time and frequency domain diagram of a continuous signal.

The four points A, B, C, and D were monitored in turn, and the variation of thermal stresses in the regulating stage, the front slot of the regulating stage, and the leaf root can be seen. It can be seen from Figure 3 that the maximum stress value appears at point A with a maximum stress value of 446.24 Mpa during the entire start-up of the rotor. The maximum thermal stress appears in the rotor after medium-speed preheating. As the speed increases, the derivative of the external surface temperature increases. By analyzing the thermal stress value of the starting process, it was found that the maximum thermal stress was far from the limit stress value, which led to a long starting process time, a too smooth starting curve under the initial conditions, and poor starting efficiency of the whole unit [23]. During the start-up of the unit, the start-up time of the unit was too long and the original start-up plan was conservative. During the starting process, the rotor is greatly influenced by the temperature, and the temperature derivative is proportional to the thermal stress. Therefore, reasonably shortening the start-up time and appropriately increasing the life loss of the turbine rotor can reduce the energy consumption during the start-up process while supplying power to the outside world

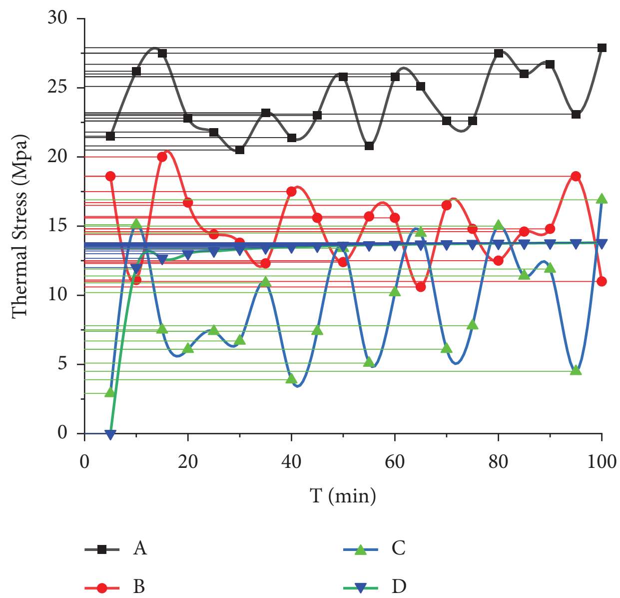

Figure 3: Stress curve of turbine rotor in thermal power plant.

faster, thus improving the efficiency index of the power plant. Through the interconnection and interactive mapping between the physical space and the digital space of the digital twin technology, a full-element, hyper-realistic digital twin of the transformer is established in the virtual space to simulate the running state of the physical entity in real-time, to achieve the purpose of online monitoring.

4. Analysis of Results

4.1. Digital Twin Model Performance Testing. The first is the cost of equipment downtime, including planned downtime and sudden failure downtime, maintenance can reduce downtime, but the need for downtime for maintenance, and failure will cause equipment downtime, so frequent maintenance and inadequate maintenance will lead to higher downtime costs. Second, is the need for some maintenance preparation in equipment maintenance, such as parts spare parts Based on this, the maintenance cost can be decomposed into four parts, maintenance preparation cost C_i^p, parts fixed cost C_i^k, performance waste cost C_i^r, and downtime loss cost C_i^s. In a period, now if a component is the first to reach its preventive maintenance threshold, preventive maintenance is performed on it, and it is judged whether to perform maintenance simultaneously or in combination with other components. Therefore, economic relevance and structural relevance are introduced, where economic relevance is used to refer to the possible overlap of repair preparation costs in maintenance, and structural relevance is used to refer to the part of the maintenance process in which there is an overlap of time in the repair process.

$$\beta_i = \sum_{i=1}^{N} (w_{hi} + 2). \quad (5)$$

The experiments are carried out by wavelet denoising of the original signal generated from the rotor operation process and then input to the deep learning neural network model after sampling and cropping. To further verify the performance of the proposed algorithm, the CNN network for bearing fault diagnosis, the Bi GRU network for bearing and gear life prediction, and the CBLSTMs network for tool life prediction are implemented and compared with the CABGRUs deep learning neural network proposed in this article, and the same training parameters are set for the four models during training. The specific training results of the models are shown in Figure 4. Digital twin technology can make the manufacturing process more “digital” and “transparent,” which has important practical significance for enterprise production process optimization, cost reduction and efficiency improvement, and quality improvement, and plays a substantial role in promoting traditional manufacturing to intelligent manufacturing.

The loss function value of the training set of the network model decreases with the increase of the number of iterations and eventually stabilizes, and the loss function value of the validation set fluctuates periodically. The accuracy of the validation set of CNN and Bi GRU network models were 89.75% and 88.02%, respectively, with low prediction accuracy, indicating that the deep learning network alone can predict the rotor wear state, but it cannot capture the deeper features hidden in the rotor operation vibration signal due to the limitation of the network model capability [24]. Compared with the deep CBLSTMs network model, the CABGRUs network model proposed in this article achieves higher prediction accuracy. CBLSTMs construct a two-layer Bi LSTM network, using bi-directional LSTM network access to access past and future information, i.e., it can extract timing signal features from both forward and reverse directions simultaneously, mining richer information features. The accuracy of the validation set is stable above 96%, and the accuracy is 96.75% after 50 iterations.

$$y_j^k = f\left(x_{j+\beta}\right) + f\left(x_i + \theta\right). \quad (6)$$

Firstly, we need to input the training set to the BP neural network model, normalize the data, and map the data of different types and scales to the same range of values. If the error is less than the set error value or has reached the set number of iterations, the weight matrix of each layer is output to end the neural network model training, otherwise, the weight matrix of each layer is updated using the gradient descent method to repeat the model training until the mean square error of the output value is less than the set error value. After completing the model training, the disordered test set is substituted into the neural network for validation, and the error between the predicted and expected values is compared, and the results are shown in Figure 5.

The Unity3D engine provides a Transform component to transform the geometry of each object in the virtual scene, including translation, rotation, and scaling of the object. To reduce the motion delay of the devices in the virtual scene of the production line, this article implements the geometric motion behavior of the devices in the 3D virtual

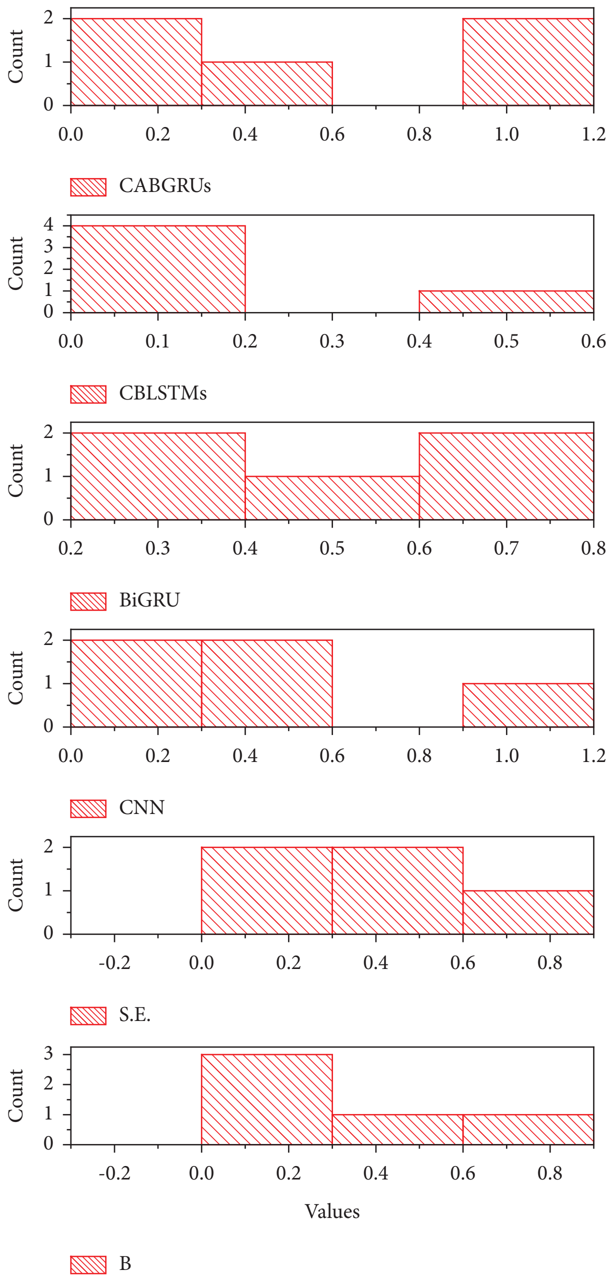

Figure 4: Model training comparison results.

environment by calling the Update function and combining the local position and localEulerAngles methods. The Update method can update the position of the equipment in the virtual scene of the production line every frame, thus improving the real-time operation of the virtual monitoring system. Firstly, the collected real-time data of the production line equipment are transferred to the virtual scene of the production line, and then the Update method is used to update the values of the local position and localEulerAngles properties under the Object Transform component in real-time so that the production line equipment can perform geometric motion in the virtual scene and achieve the purpose of synchronizing the virtual production line with the physical production line. The UGUI component of the

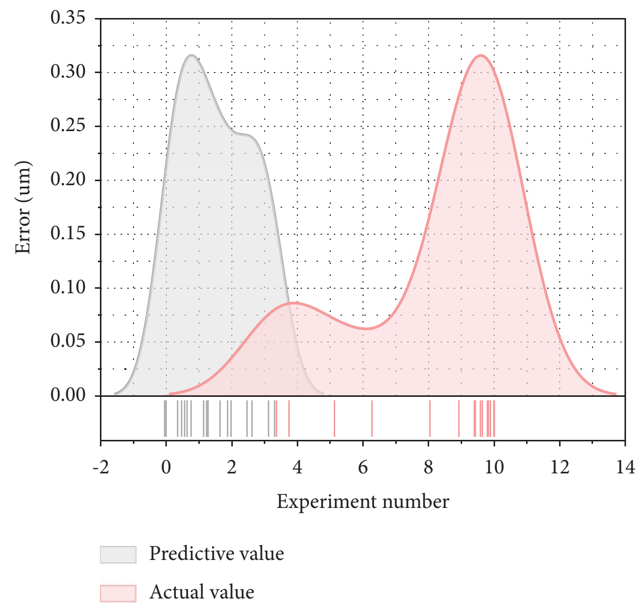

Figure 5: Training results of the digital twin model.

Unity3D engine is used to realize the visual display of the device status data. By analyzing the geometric transformation relationship of the 3D model of the equipment in space, the motion control of the equipment model in the virtual scene of the production line is completed based on the Unity3D engine and real-time data.

4.2. Simulation Test of the Turbine Rotor Automation Monitoring Model for Thermal Power Plants. The ACLMD method is used to extract features from the vibration signals of seven typical turbine faults (rotor unbalance, rotor misalignment, bearing seat looseness, oil film oscillation, rotor crack, oil film vortex, and bearing wear). It should be noted that considering a large amount of sample data for classifier training and testing, 10 sets of vibration signals are extracted for each of the seven typical faults, and the energy entropy of the PF component of each set of vibration signals is calculated separately. The $a, b, \ldots, g$ English numbers are used to mark the different fault states; the $1, 2, \ldots, 6$ numbers are used to mark the energy entropy of the 6 PF components decomposed from each fault state; the Roman numerals I, II, ..., X is used to mark the different groups of signals. For example, the energy entropy of the first PF component of the fifth set of data for the third set of loose bearing seat faults can be represented by Ve1. To further illustrate the feasibility of using energy entropy as a feature quantity for fault pattern recognition, the energy entropy of PF components in different fault states of the turbine is analyzed separately for variability and repeatability. As shown in Figure 6, the variability of the energy entropy of PF components under seven states is shown (taking the first set of signals as an example).

As a result, the energy entropy of different fault PF components is significantly different, and the entropy value in a specific frequency band is much larger than that in other

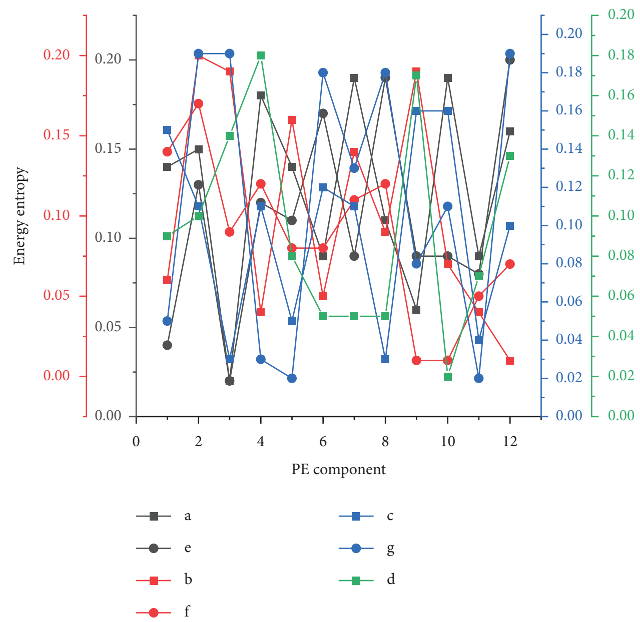

Figure 6: Differences in the energy entropy of PF components in the seven states.

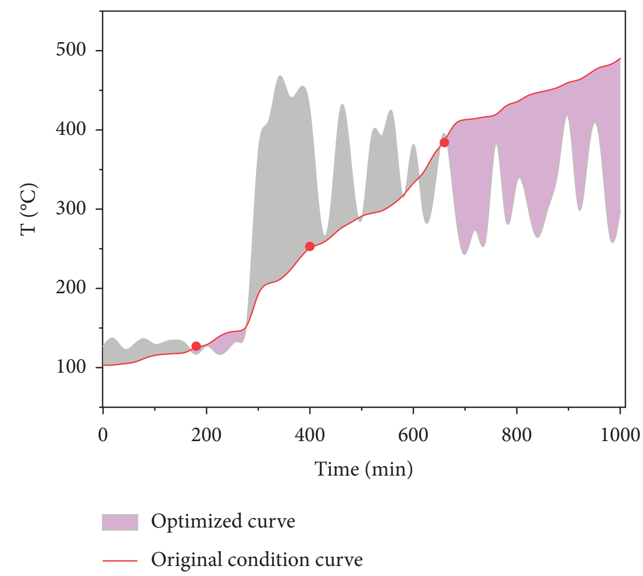

Figure 7: Comparison of start-up time curves before and after optimization.

frequency bands when a fault occurs and the entropy values of different components in the same fault state are also different, so an intelligent algorithm is needed for pattern recognition of turbine vibration faults.

The particle swarm algorithm is a stochastic search algorithm based on the collaboration of group instances developed based on the foraging behavior of birds. It is also a kind of group intelligence. The particle swarm algorithm is an evolutionary algorithm [25]. The nature of the evolutionary algorithm is an adaptive algorithm. It is an evolutionary algorithm that compares the solution of an optimization problem with the solution of an individual and applies it to the recombination, selection, and mutation of the solution during optimization. By simulating the reproduction, compilation, and competition of organisms to reflect the optimization problem, the variables are continuously updated and the optimal solution is finally obtained. This section uses the Particle Swarm Optimization (PSO) algorithm to obtain a set of start-up time parameters. With the optimal cold start parameters, the start-up time of the unit under the original conditions was reduced by 32 min or 5.3%, and the temperature part of the optimized start-up curve was changed. The steam turbine is responsible for the key equipment that converts thermal energy into mechanical energy and then into electrical energy. Under the working environment of high speed, high stress, and high temperature, the components bear a large load and are often subjected to various alternating stresses. The rotor stresses during the new start were calculated using ANSYS software. the positions of the four monitoring points were kept constant and the stress results are shown in Figure 7. From Figure 7, the maximum stress value of the rotor under the new starting scheme is 464.72 MPa, which occurs during the temperature rise period after the medium-speed turbine warm-up. The thermal stress of the turbine rotor changes as the temperature rises at the rate of the turbine, and the temperature difference on the surface starts to become larger after the temperature rise rate is large, and the drastic temperature change will directly affect the size of the thermal stress worth of the turbine rotor, that is, the thermal stress of the turbine rotor increases when the temperature rise rate changes a lot.

The image of the stress field clearly shows the location of the stress concentration, which is mainly at the root of the turbine rotor blade. According to the above data, the time parameters after the adaptive particle swarm optimization meet the accuracy requirements. According to the optimized starting scheme, the whole starting process of the unit is shortened by 32 mins, and the unit load is greatly increased. The optimization results are satisfactory. It reduces the start-up time and energy consumption of the unit, ensures the safety of the unit, improves the economy, and further increases the efficiency of the plant. The time parameters after particle swarm optimization meet the accuracy requirements. According to the optimized start-up plan, the entire start-up process of the unit was shortened by 32 min and the unit load was greatly increased. The optimized start-up scheme was verified using ANSYS software. The stress value of the maximum stress concentration point of the turbine rotor meets the requirements.

5. Conclusion

Based on digital twin technology, this article develops a real-time data-driven virtual monitoring system for turbine rotor operation in thermal power plants. By building a physical rule fusion model of rotor operation and establishing a geometric behavior mapping method for rotor operation in virtual scenarios, the physical state monitoring, and abnormal rotor operation state prediction are realized. Finally, by analyzing the geometric transformation relationship of the 3D model of the equipment in space, the motion control of the equipment model in the virtual scene of the production line is completed based on the Unity3D engine and real-time data, and the collision detection of the equipment in motion is realized by building the collision body of the equipment in the virtual scene. This provides a theoretical approach to realizing the digital twin of the device at the geometric level. The real-time physical data of rotor operation is uploaded into the digital twin, where the real-time status information is used for dynamic updating of the digital twin, and the rotor operation fault gas data is diagnosed through the fault diagnosis model stored in the behavioral model of the digital twin, and the rotor operation fault results and the maintenance plan are displayed on the system interactive interface for reference and timely maintenance by engineers. Although this article has studied the fault diagnosis of turbine rotor operation in thermal power plants based on digital twin, optimized the relevant algorithms, performed experimental verification, and finally designed the fault diagnosis system, some issues need to be further investigated due to time constraints. The application of data science and simulation technology in this article is not sufficient, and further consideration of the application scenarios and matching of data science and simulation technology in manufacturing unit control is needed.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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