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Data Super-Network Fault Prediction Model and Maintenance Strategy for Mechanical Product Based on Digital Twin

ZHIFENG LIU, WEI CHEN, CAIXIA ZHANG, CONGBIN YANG, AND HONGYAN CHU
Institute of Advanced Manufacturing and Intelligent Technology, Beijing University of Technology, Beijing 100124, China
Beijing Key Laboratory of Advanced Manufacturing Technology, Beijing University of Technology, Beijing 100124, China

Corresponding author: Caixia Zhang (zhang-cx15@bjut.edu.cn)

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ABSTRACT When mechanical products work in complex environments, it is imperative to build an optimal maintenance strategy, based on accurate positioning of fault locations and prediction of fault conditions. Based on digital twinning technology, this paper proposes a ''super-network-warning features'' fault prediction and maintenance method. According to the digital twin five-dimensional structure, a three-layer super-network model is constructed, providing a quantitative research for data among heterogeneous subjects in digital twinning. Early-warning-features in the physical layer, virtual layer and service layer are selected as input parameters of the fault prediction model to accurately predict the cause of the fault. Then, using the simulation and optimization functions of the virtual model in digital twinning, a real-time maintenance strategy is formulated for the causes of the fault. It supplements the missing link between fault prediction and maintenance. Taking an aero-engine bearing as an example, this method is compared with a traditional method. The results show that the model prediction error of this method is better than the traditional method.

INDEX TERMS Digital twinning, data super-network, fault prediction, maintenance strategy.

I. INTRODUCTION

Manufacturing technology is continuously improving [1], while more and more mechanical products operate, for long periods of time, in various complex environments (e.g. Bearings, marine propulsion, robots). Due to the intricate environmental factors, mechanical products will inevitably fail, during operation. However, maintenance in complex environments requires high costs, which has turned the problem of product fault prediction and maintenance into a research hotspot, in recent years. On the one hand, mechanical products are extremely difficult or even impossible to repair, in complex environments. Even if repair is possible, locating faulty parts and constructing a corresponding maintenance strategy, in time, are not possible, leading to waste of money and resources. Furthermore, the accuracy of prediction is reduced, when using product manufacturing data, for fault prediction, because the data is highly susceptible to interference from other sources of vibration.

With the continuous development of information physics systems, digital twinning technology provides new solutions for fault prediction and maintenance of mechanical products. Digital twin [2] is an intelligent, interdisciplinary and multi-model based technology that gathers big data. The characteristic of digital twin technology is to reflect the working process of physical entity in real time through virtual model. At the same time, the next work can be simulated in advance. And then guide the working process of physical entities. By combining digital twinning technology and fault prediction and maintenance, some of the present problems, in this field, are solved, making it possible for mechanical products, to develop intelligently.

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II. OVERVIEW OF DIGITAL TWIN, SUPER-NETWORK, FAULT PREDICTION AND MAINTENANCE

Many scholars, all over the world, have done a lot of research on fault prediction and maintenance. Xiao Cheng et al. [3]

present a new method developed, using radar chart and Support Vector Machine (SVM) approach, for fault diagnosis and prediction of wind turbine pitch system. Zhou *et al.* [4] developed a fault diagnosis approach, for fuel regulator of aircraft engine. To build an exact mathematical engine inverse model, an emerging machine leaning technique, called relevance vector machine, is adopted, to establish the relationship between sensor readings and fuel consumption. Qi *et al.* [5] proposed a stacked Sparse Autoencoder (SAE)-based fault diagnosis method. Cheng *et al.* [6] proposed an enhanced particle filtering algorithm, for the remaining useful life prediction of wind turbine drivetrain gearboxes. Prakash *et al.* [7] present a probabilistic approach for fault detection and prognosis of rolling element bearings, based on a two-phase degradation model. Wang *et al.* [8] proposed empirical wavelet transform, for extracting bearing fault features, formulated as a constrained optimization problem.

The above scholars have made great achievements in the research of fault prediction and maintenance, but some issues still remain under investigation. ① The research of fault prediction and maintenance mostly focuses on prediction, while seldom combines prediction with maintenance. ② There are some optimization algorithms, adopted in fault prediction, but, as the developed model becomes more complex, the role of these algorithms is gradually degrading. ③ According to the failure prediction results, failure maintenance strategies cannot be effectively formulated.

Since the "Digital Twin" appeared, its application has gradually evolved, from product predicting, to product predicting, maintenance and service, making it possible to solve the aforementioned problems. Product predicting: The US Air Force Research Laboratory Structural Science Center combines high fidelity flight model with calculation model, affecting the flight structure deviation and temperature, based on digital twin technology, to predict the life span [9]. The US Air Force research laboratory uses physical entities, to evaluate high-fidelity virtual models and predict the problem of aeronautical thermal coupling elasticity [10]. Product predicting and maintenance: Grieves and Vickers [11] studied the application of digital twin in fault prediction and elimination, in complex systems. Hochhalter [12] detected the operational status of the spacecraft, in real time, by combining digital twinning with sensory particle technology. General Electric (GE) [13] attempted to achieve real-time monitoring and predictive maintenance of industrial engines, using digital twinning technology. Product predicting, maintenance, and service: PTC has built an interaction model, between the real world and the virtual world, to provide users with efficient after-sales service [14]. Dassault has established a digital twin 3D interactive platform, to continuously improve products, in the virtual world, based on feedback from user experience information [15]. Siemens has built a virtual model of the production process, to digitize the enterprise [16]. Alam and El Saddik [17] present a digital twin architecture reference model, for the cloud-based CPS, C2PS. The model can be used to identify basic and hybrid computation-interaction modes, in different degrees. Fei and Zhang [18] proposed the concept of digital twin workshop, realizing the interaction and integration of physical and virtual workshops.

The rapid development of digital twinning technology is tightly connected to the emergence of new Information Technologies (ITs) [19] (e.g. Internet of Things, cloud computing and artificial intelligence). The new ITs enable Wireless Sensor Network (WSN) and Radio Frequency Identification (RFID) technologies, to be widely used, in the collection of real-time data [22], [23] (e.g. production factors [20], materials [21]). The collected data drive the development of the automated manufacturing industry [24], [25] and provide technical support to the in-depth study of digital twinning. Zhuang *et al.* [26] proposed a digital model framework, for intelligent production management and control, in complex product assembly workshops, based on real-time data. Woo *et al.* [27] developed a big data analysis platform, for the manufacturing system, realizing the interconnection between data. Furthermore, other researchers also discussed the application of big data in product maintenance [28], fault detection [29], fault prediction [30], risk assessment [31] and other fields.

Due to the multi-dimensional and multi-modal characteristics of data among different subjects, in the digital twin model, it is necessary to use some technologies to realize the transformation from qualitative research to quantitative research among different subjects.

Super-network is a multilayer network with large scale, complex connections and various nodes. Nagurne and Wakolbinger [32] defines super-networks as networks, superior to existing networks and of higher order. Compared to ordinary complex networks, super-network has the characteristics of multi-level, multi-attribute or multi-criterion [32], [33]. Super-network is used to describe the interaction and influence between networks [34].

This paper uses the known new technology (e.g. Neural network, Density-based data preprocessing algorithm, Feature matrix clustering), to combine the advantages of digital twinning and super-networks. According to the fast response of fault prediction results, a method, integrating fault prediction and maintenance, is formed. At the same time, the method solves the problems of fault prediction and fault location accuracy and optimality of maintenance strategy. The application framework and workflow of this method are described in detail in the following sections.

III. DATA SUPER-NETWORK MODEL BASED ON DIGITAL TWINS

A. DATA-BASED THREE-LAYER SUPER-NETWORK MODE

The core of digital twin is the model and data. In order to deepen the research into digital twin theory and promote its application in the whole life cycle of products, the team of Beihang University developed the digital twin model as a five-dimensional structural model [38], based on years of research in intelligent manufacturing services, logistics and big data [35]–[37]. The model includes Physical Entity (PE), Virtual Model (VM), Service System (Ss), Digital twin Data (DD) and Connection (CN). PE, VM and Ss can interact with each other. The information among PE, VE and Ss is transmitted to DD through data stream. DD drives PE, VE and Ss, as shown in Fig.1.

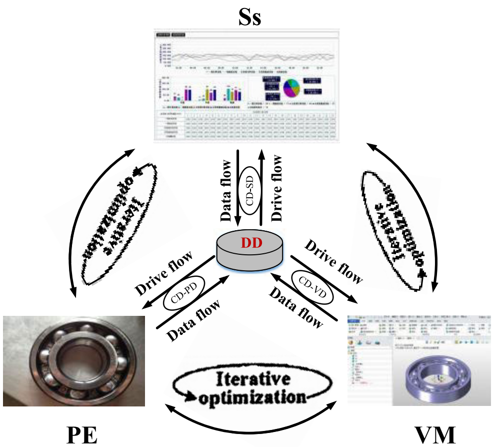


FIGURE 1. Data three-layer super-network model [38].

In this paper, the digital twin five-dimensional model contains three kinds of elements: physical entity, virtual model and service system, each of which is a node of different nature. The data, stored in the resource pool, is a dynamic set, due to the continuous addition of new data. In the process of production and operation of physical entities, there is a coordination relationship among them. Looping relationships are between virtual models, through their continuous optimization. There is a controlling relationship among the service systems, due to their function in sequence. Physical entities are simulated by virtual models, while the virtual model works through a series of service systems. There is a pairwise relationship between them. The features above cannot be clearly expressed in ordinary complex networks. Therefore, the functional elements of data are studied from the perspective of multi-level, multi-dimension and multi-criteria, by means of super-networks. The three types of elements, in the super-network data, are both independent and interrelated. The construction of super-network model includes two aspects: 1) the mathematical model of each sub-network layer, 2) the mapping relationships between sub-network layers.

B. CONSTRUCTION OF DATA SUPER-NETWORK MODEL

1) CONSTRUCTION OF SUB-NETWORK MODELS FOR DATA SUPER-NETWORKS

Data super-network consists of three sub-networks: data physical layer, data virtual layer and data service layer.

(1) Data physical layer (SN_{PE})
The network model of SN_{PE} is expressed as:

$$SN_{PE} = (N_{PE}, E_{PE-PE})$$

where, $N_{PE} = \{p_1, p_2, \cdots, p_i, \cdots, p_k\}$ represents the set of nodes in the network and k represents the number of nodes.

$$E_{PE-PE} = \left\{ep_{12}, ep_{13}, \cdots, ep_{\mathrm{ij}}, \cdots, ep_{(k-1)k} \,\middle|\, ep_{\mathrm{ij}} = (p_i, p_j)\right\}$$

represents the set of edges in the network, ep_{ij} is the relationship between nodes p_i and p_j.
Node is the index data of the product during operation. For example, in physical layer super-network, node p_i refers to the i-th running physical workshop production factor data. The nodes in each layer of sub-network are connected to each other due to specific correlation, as a result, they form the edge of the sub-network. For example, in the physical layer super-network, different accelerations of products will result in different vibration frequencies, which will further affect the wear of products.

(2) Data virtual layer (SN_{VE})
The data virtual layer network SN_{VE} is the second sub-network. The network is used to describe the virtual model system, corresponding to the data physical layer. The network model is expressed as:

$$SN_{VE} = (N_{VE}, E_{VE-VE})$$

where $N_{VE} = \{v_1, v_2, \cdots, v_i, \cdots, v_k\}$ represents the set of nodes in the network and k represents the number of nodes.

$$E_{VE-VE} = \left\{ev_{12}, ev_{13}, \cdots, ev_{\mathrm{ij}}, \cdots, ev_{(k-1)k} \,\middle|\, ev_{\mathrm{ij}} = (v_i, v_j)\right\}$$

represents the set of edges in the network, ev_{ij} is the relationship between nodes v_i and v_j.

(3) Data service system (SN_{Ss})
The data service layer network SN_{Ss} is the third sub-network. The network is used to describe the service application system, corresponding to the data physical layer or the data virtual layer. The network model is expressed as:

$$SN_{Ss} = (N_S, E_S)$$

where, $N_S = \{s_1, s_2, \cdots, s_i, \cdots, s_k\}$ represents the set of nodes in the network and k represents the number of nodes.

$$E_{S-S} = \left\{es_{12}, es_{13}, \cdots, es_{\mathrm{ij}}, \cdots, es_{(k-1)k} \,\middle|\, es_{\mathrm{ij}} = (s_i, s_j)\right\}$$

represents the set of edges in the network, es_{ij} is the relationship between nodes s_i and s_j.

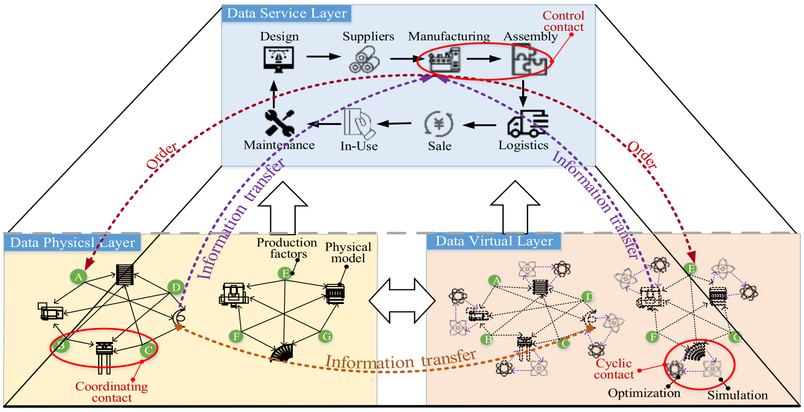


FIGURE 2. **Data three-layer super-network model.**

2) MAPPiNG RELATIONSHIP BETWEEN SUB-NETWORK OF DATA SUPER-NETWORKS

a: RELATIONSHIP MAPPING BETWEEN SUB-NETWORKS

The physical entity (SN_{PE}), the virtual model(SN_{VE}), and the service system (SN_{Ss}) complement each other. Separate sub-networks are aggregated, to form a data super-network with three nodes. The entire life cycle of the product is reflected and interconnection between data is achieved.

① Mapping between data physical layer sub-network (SN_{PE}) and data virtual layer sub-network (SN_{VE}).

In the digital twin five-dimensional model, each physical entity corresponds to a virtual model. In the super-network, each physical entity in the SN_{PE}, must have a one-to-one mapping relationship with a virtual model, in SN_{VE}.

The mapping relationship is expressed as:

$$M_{PE-VE} = \left\{\left(PE_j\ ,\ VE_k\right) |\mathrm{j} \in SN_{PE}, \mathrm{k} \in SN_{VE}\right\}$$

② Mapping between $SN_{PE}(SN_{VE})$ and SN_{Ss}.

The service system can run effectively because of the mapping between physical entity and virtual model. In the digital twin five-dimensional model, the data, collected by each physical entity (or virtual model), corresponds to the functional mode of one or several service systems. At the same time, data, in a service system, is collected by multiple physical entities (or virtual models). or are inevitably mapped to the functional modes of several service systems, in.

The mapping of SN_{PE} to SN_{VE} is expressed as:

$$S\left(PE_i\right) = \left\{S_i\ |S_i \in S,\ \varphi\left(PE_i, \mathrm{S}_j\right) = 1\right\}$$

Among them, $S\left(PE_i\right)$ represents a set of service modes corresponding to physical entity PE_i. $\varphi\left(PE_i, \mathrm{S}_j\right) = 1$ denotes the relationship between PE_i and S_j, that is, the service system mode S_j corresponding to PE_i, $j = 1, 2, \cdots, n$, where n denotes the number of service systems, corresponding to the physical layer.

The mapping from the data service layer to the data physical layer is expressed as:

$$PE\left(S_i\right) = \left\{PE_i\ |PE_i \in PE,\ \mu\left(\mathrm{S}_i, PE_j\right) = 1\right\}$$

Among them, $PE\left(S_i\right)$ represents a collection of physical entities, required by data service mode S_i. $\mu\left(\mathrm{S}_i, PE_j\right) = 1$ denotes the relationship between S_j and PE_i, that is, the physical entity PE_i required by service system mode S_j, $j = 1, 2, \cdots, n$, where n denotes the number of data physical entity models, required by service system mode.

According to the above description, a mapping relationship, between the data network layer and the data service layer subnetwork, is constructed.

$$M_{PE-S} = \left\{\left(PE_j\ ,\ S_k\right) |\mathrm{j} \in SN_{PE}, \mathrm{k} \in SN_{Ss}\right\}$$

The mapping relationship between the data virtual layer and the data service layer is similar to the above network relationship, so it is not described here.

b: FORMAL REPRESENTATION OF SUPER-NETWORKS

According to the mapping relation between each subnetwork of the data super-network constructed above, the data super-network model is expressed as:

$$\begin{aligned} SN &= \left(SN_{PE}, SN_{VE}, SN_{Ss}, M_{PE-VE}, M_{PE-Ss}, M_{VE-Ss}\right) \\ &= \left(PE, VE, Ss, M_{PE-VE}, M_{PE-Ss}, M_{VE-Ss}\right) \end{aligned}$$

As mentioned above, the purpose of building a data super-network model is to analyze the correlation between the data, to predict product faults and perform respective repairs. The data from the three-layer super-network model are shown in Fig.2. The virtual model of physical entity is established by digital twin technology. By using the super-network technology, the data super-network model of physical layer, virtual layer and service layer is established. Virtual model is a faithful mirror image of physical entities, and has simulation and optimization functions for each physical model. The data needed in the manufacturing process of the data service layer comes from the physical layer and the virtual layer. At the same time, the manufacturing process can also give instructions to the physical layer and the virtual layer.

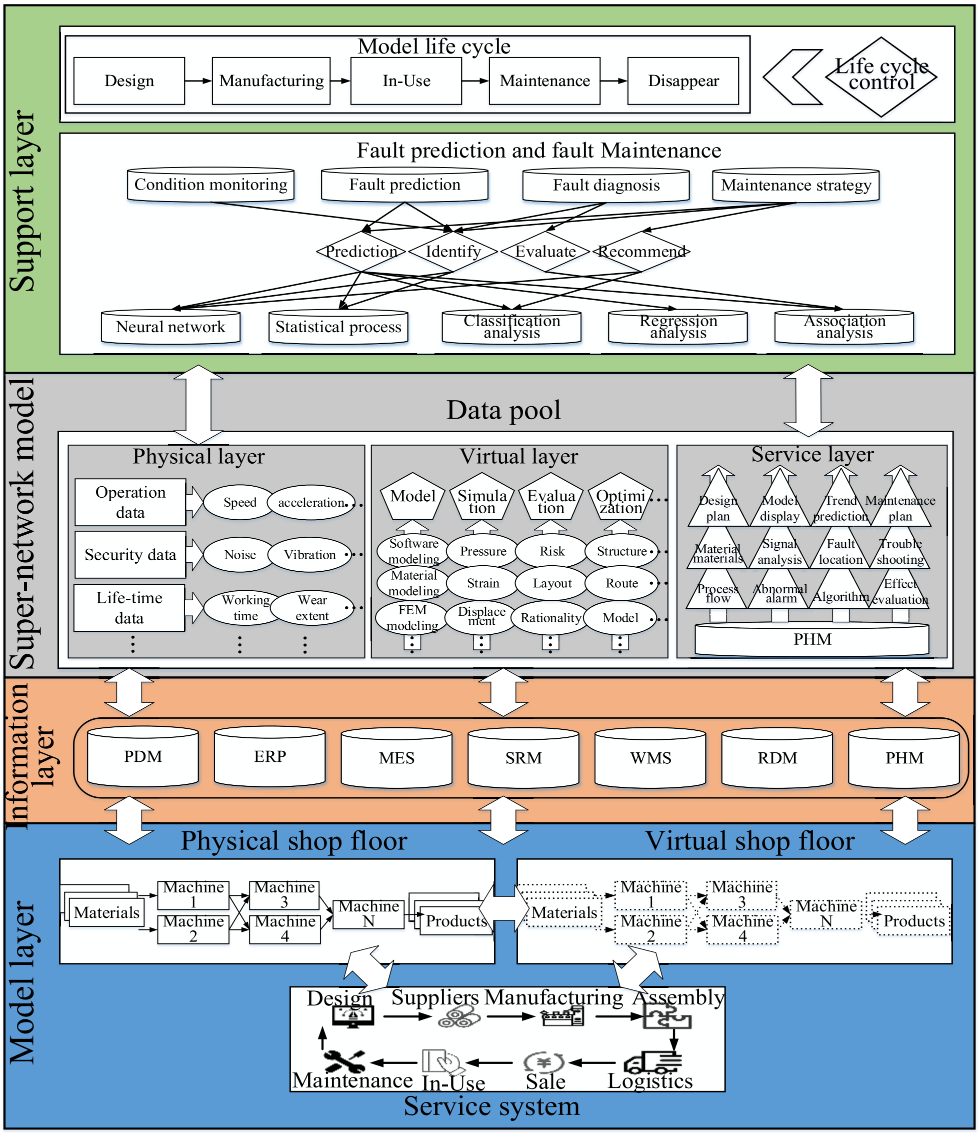


FIGURE 3. Product fault prediction and maintenance strategy detailed architecture.

IV. FAULT PREDICTION AND MAINTENANCE STRATEGY FOR MECHANICAL PRODUCTS

Fig.3 shows the detailed architecture of the mechanical product failure prediction and maintenance strategy, including model layer, information layer, super-network model layer and support layer. Specifically, the model layer and the information layer collect the data, in the digital twin five-dimensional model, by means of collection method, and pre-processing data. Data is classified hierarchically, through a super-network model. The support layer is based on the information from data mining, to predict and maintain faults. The following section includes a detailed description.

A. DATA ACQUISITION AND DATA PREPROCESSING PHASE

The collected data are stored in the super-network model, classified and fused effectively. In the data physical layer, those required to be collected, are mainly the Operation data (pod), Security data (psd) and Life-time data (pld) of mechanical products. Operation data include acceleration, voltage/current, speed and other data; Security data include noise, vibration, temperature rise and other data; Life-time data include working time, wear extent and other data. The mathematical model is expressed as $PE = (pod, psd, pld)$. In the data virtual layer, data mainly include product model data and virtual operational data (e.g. Model (md), simulation (sd), evaluation (ed), optimization (od), prediction (pd)). The mathematical model is expressed as $VE = (md, sd, ed, od, pd)$. In the data service layer, data includes full lifecycle service data for mechanical products, from top-level management to bottom-level production control (e.g. design service (dsd), material supply chain service (mscd), manufacturing service (msd), assembly service (asd), transportation service (tsd), sale service (ssd), use service (usd), after-sale service (a-ssd) and cycle service data (csd)). The mathematical model is expressed as $Ss = (dsd, mscd, msd, asd, tsd, ssd, usd, a-ssd, csd)$.

In a fusion system, based on a single criterion, it is difficult to collect, store and make decisions on twin data. The three layers of data are interconnected, through a super-network model, to realize the classification and encapsulation of multi-type data.

The data in the super-network has the characteristics of multiple types, large time scale and inconsistent granularity. First, density-based data preprocessing algorithm is implemented, to find the abnormal data [39]. Specifically: given a data set N, object a, b, and positive integer k, the neighborhood radius of object a is defined as $dist_k(a)$, which $dist_k(a,b)$ is the distance between a and b, the k-distance neighborhood of a is defined as $N_k(a) = \{b\,|b \in N, dist_k(a,b) \leq dist_k(a)\}$.

The local reachability density of point a is expressed as:

$$lrd_k(a) = \frac{\|N_k(a)\|}{\sum_{b\in N_k(a)} \max\{dist_k(a), dist_k(a,b)\}}$$

The local outlier factor for point a is expressed as:

$$LOF_k(a) = \frac{\sum\limits_{b\in N_k(a)} \frac{lrd_k(b)}{lrd_k(a)}}{\|N_k(a)\|} = \frac{\sum\limits_{b\in N_k(a)} lrd_k(b)}{\|N_k(a)\|} / lrd_k(a)$$

The local outlier factor is the average of the ratio of $lrd_k(N_k(a))$ to $lrd_k(a)$. If the ratio is larger than 1, the more likely it is the abnormal point. The data points with the highest anomaly score of 20% are regarded as outliers (After a period of time analyzing the data, we found that the probability of outliers is about 2%. From these outliers, we also found that only 20% of them are erroneous data.). Then, the value is compared with the original experimental record data to determine whether it is deleted (human error or laboratory record error can be deleted).

Then, the remaining clean data are clustered by using the feature distance formula, in order to improve the accuracy of fault prediction and provide a basis for the selection of input parameters in fault prediction. Four eigenvalues are analyzed: euclidean distance between data λ_1, euclidean distance between data mean λ_2, euclidean distance between data variance λ_3 and euclidean distance between data peaks λ_4. The eigenvalue matrix is constructed to solve the eigenvalue distance between data λ. Let the number of data in an acquisition cycle, be M, while the number of collection points be N. Then, the b-th sample data of the a-th collection point is ψ_{ab}. Among them, $a \in [1, N], b \in [1, M]$, the eigenvalue calculation method is as follows.

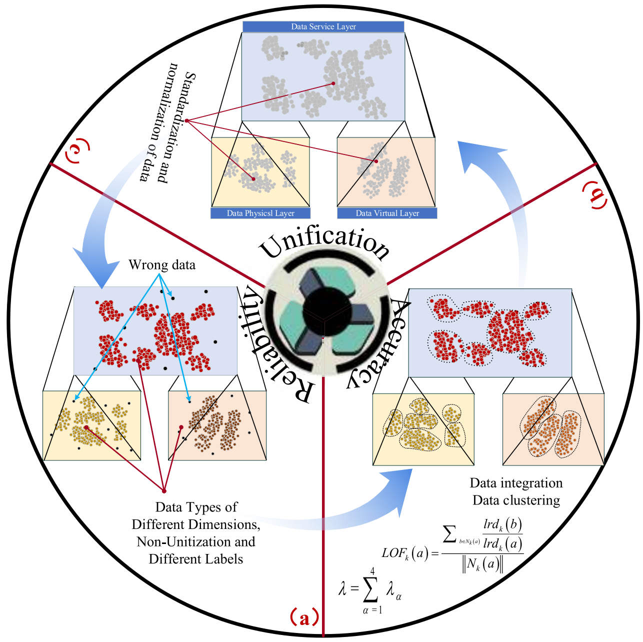


FIGURE 4. Super-network data preprocessing process.

$$\begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \\ \lambda_4 \\ \lambda \end{bmatrix} = \begin{bmatrix} \dfrac{\sum\limits_{a=1,i=1}^{M}\sum\limits_{j=1}^{N}\left|\psi_{ib}-\psi_{jb}\right|}{N(N-1)M} \\ \dfrac{\sum\limits_{i,j=1}^{N}\left|\sum\limits_{b=1}^{M}\psi_{ib}-\sum\limits_{b=1}^{M}\psi_{jb}\right|}{M} \\ \dfrac{\sum\limits_{i,j=1}^{N}\left|\sum\limits_{b=1}^{M}\left(\psi_{ib}-\overline{\psi}_i\right)^2-\sum\limits_{b=1}^{M}\left(\psi_{jb}-\overline{\psi}_i\right)^2\right|}{M} \\ \sum\limits_{b=1}^{M}\left|\psi_{i\max}-\psi_{j\max}\right| \\ \sum\limits_{\alpha=1}^{4}\lambda_\alpha \end{bmatrix}$$

Finally, the data in the super-network is unitized and transformed into a dimensionless pure value. Not only a unified description of the data is achieved, but also data of different magnitudes can be compared. The super-network data preprocessing phase is shown in Fig.4 ((a) The process uses density-based algorithms to detect outliers. (b) The process uses clustering algorithm for clustering. (c) The process is to standardize the data).

B. FAULT PREDICTION

The same type of clustering data in the super-network is called a data label. After analyzing the vibration signal data, a series of features of the signal can be obtained. The difficulty of fault prediction will increase, if all the features

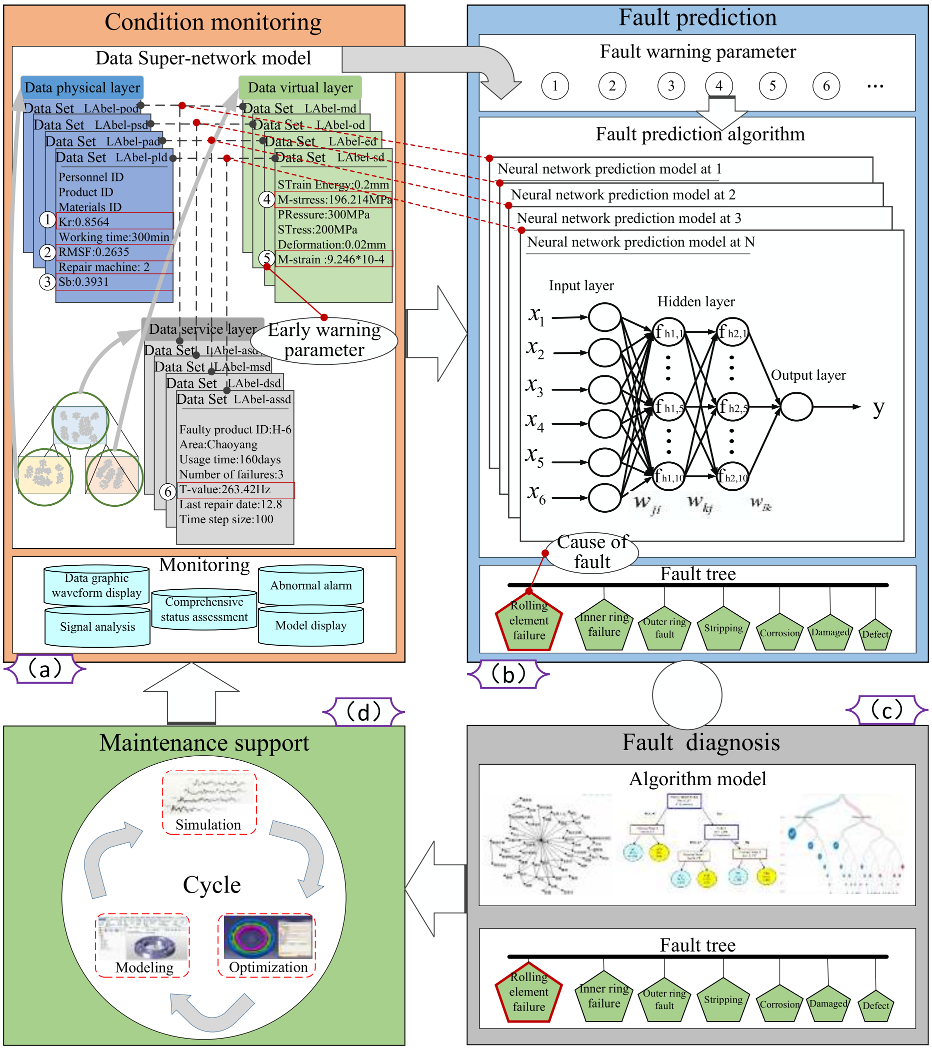


FIGURE 5. **Fault prediction and maintenance strategy model for mechanical products.**

are considered as the input. So, it is necessary to use only the representative features of the signal, as the input of the model, for fault prediction purposes. The representative features of the signal can best represent the data signal. In this paper, the input, to the aforementioned fault prediction model, is called the early-warning-features. According to the fault prediction results, corresponding maintenance strategies are formulated.

(1) Data set preparation: The data set consists the input and output of the predictive model. The early-warning-features of the signal is selected as the input parameters to the model in the super-network of physical layer, virtual layer and service layer, based on the data label of historical fault. The historical fault result is used as the output of the model, as shown in Fig.5(a).

(2) Fault prediction: The aspect of fault prediction can be solved by two kinds of methods: fault prediction and fault diagnosis. 1) Fault prediction is about predicting the output of key indicators, through the input of early-warning-features, based on the predicted model. It can be divided into machine learning method or statistical analysis method. Machine learning can be realized by machine learning techniques. (e.g. support vector machine, bayesian network and artificial neural network), as shown in Fig.5(b). Statistical analysis can be realized by means of regression technique. 2) Fault diagnosis can be described as determining the cause of the fault and the fault location by means of a diagnostic algorithm, when the fault is known (e.g. Group diagnosis algorithm, genetic algorithm and particle swarm optimization algorithm), as shown in Fig.5(c).

C. FAULT MAINTENANCE STRATEGY

Maintenance strategy includes four steps: generating maintenance plan, simulation and verification of maintenance plan, re-optimizing maintenance plan, and implementing maintenance plan by physical model. The maintenance strategy implementation process is illustrated, based on a case of gear failure prediction. If the predicted results of the fault regards tooth root damage, the fault should be repaired by welding. 1) According to the predicted damage degree and damage position of the tooth root, the welding path of the welding robot is adjusted. The welding software is stored in the robot's operating system. 2) The procedure is validated in the virtual model, before the physical model executes the welding procedure. The working environment of the welding robot is simulated in the virtual model. Then, the robot executes a procedure, to verify the maintenance plan. 3) The physical entity performs the welding route for maintenance, when the fault is handled well. Welding procedure will be optimized, when failure handling is not good. 4) The optimized maintenance plan is transferred to the physical model, for implementation.

In terms of maintenance strategy, the standard of fault handling is determined by the fluctuation of the data signal of the fault location, during the virtual verification process. Combining the above cases: 1) The virtual model restores the working environment of the gear. The signal fluctuation value of the fault location is compared to the fluctuation threshold. The threshold is the difference between the maximum and minimum fluctuations of the faulty location, during normal operation. 2) If the fluctuation value does not exceed the fluctuation threshold, the fault processing result is good. If the fluctuation value exceeds the fluctuation threshold, the fault repair result is not good. 3) Therefore, the welding procedure is optimized, for fluctuations beyond the threshold, in order to limit the signal fluctuation value within the threshold range, as shown in Fig.5(d). The optimization process is completed by using the path optimization algorithm contained in the digital twin service layer.

V. CASE STUDY

A. PROBLEM DESCRIPTION

Aero-engine is the power device of aero-aircraft. The main shaft bearing is not only the key component of aero-engine, but also its weak link, which has an important influence on the safe and stable operation of aero-aircraft. The bearing in aero-engine is different from the bearing used in ordinary mechanical devices, while its working environment is more complex. In addition, the bearing, in aero-engine, is one of the main fault sources of the aircraft. The main causes of failure are inner race, outer race and the rolling parts fault. This chapter takes an aero-engine bearing as an example, to predict and repair the three types of faults, appearing (e.g. Inner race, outer race and the rolling parts fault.), while the effectiveness of the proposed fault prediction and maintenance strategy is verified.

B. FAULT PREDICTION METHOD

As shown in Fig.6, according to the digital twinning technology in Section III.A, the virtual model of the bearing is established, based on four levels of geometry, physics, behavior and constraint, regarding the actual working conditions of the bearing.

(1) Geometric model: constructing geometric three-dimensional models of bearing components (e.g. shape, size, position, structure) (2) Physical model: physical attributes (e.g. working capacity, wear and temperature.) are added to the geometric model. Meanwhile, the stress, structure, deformation and other physical phenomena of the bearing are simulated and analyzed based on the finite element method. (3) Behavior model: on the basis of the physical model, the behavior model of the bearing working state, under complex environmental factors, is constructed. (4) Constraint model: the constraints of the bearing virtual model include inter-model constraints, (e.g. operational constraints, environmental constraints, temperature constraints, force constraints.). The virtual model can be guaranteed to work within the scope, allowed by the actual environment. Through the above four levels of structural cooperation and functional coupling, the information of the physical entity and the virtual model can be interactively integrated, to form a high-fidelity virtual image of the bearing. Then, the physical entity and the virtual model are connected to the service system, for full cycle monitoring of the operational cycle, as shown in Fig.6(a). According to the data super-network model, constructed in Sections III.B and III.C, the historical data and real-time data, during the bearing operation process, belong to different super-network layers, as shown in Fig.6(b). Finally, the hierarchical data are preprocessed and clustered according to the method in Section IV(B). For the processed data, the early-warning-features of physical layer, virtual layer and service layer are selected as the input of the fault prediction model. The clustering results are shown in Fig.6(c).

Fluctuation of the vibration signal, at the fault location, will cause significant abnormal changes, before the aero-engine bearing failure. Therefore, some early-warning-features are selected, among the altered vibration signals, for fault prediction. In the traditional fault prediction method, only the kurtosis, root mean square (RMS) frequency and frequency standard deviation of the bearing vibration frequency signal, are selected as the early-warning-features. However, due to the interference of other vibration sources, the prediction accuracy of vibration signals is greatly reduced. The prediction method of this paper is based on the data super-network model. The following six features will be selected as early-warning-features: kurtosis, RMS frequency, frequency standard deviation of data physical layer, maximum stress and strain of data virtual layer, theoretical fault characteristic frequency of data service layer. The above six early-warning-features are taken as the input parameters to the prediction model. The interference problem, existing in the traditional fault prediction approach, is avoided, increasing the prediction accuracy. Then, Extreme Learning Machine (ELM) is used as fault prediction model. Because the model has fast reaction time and is not easy to fall into the minimum point, this case builds a fault prediction model, based on

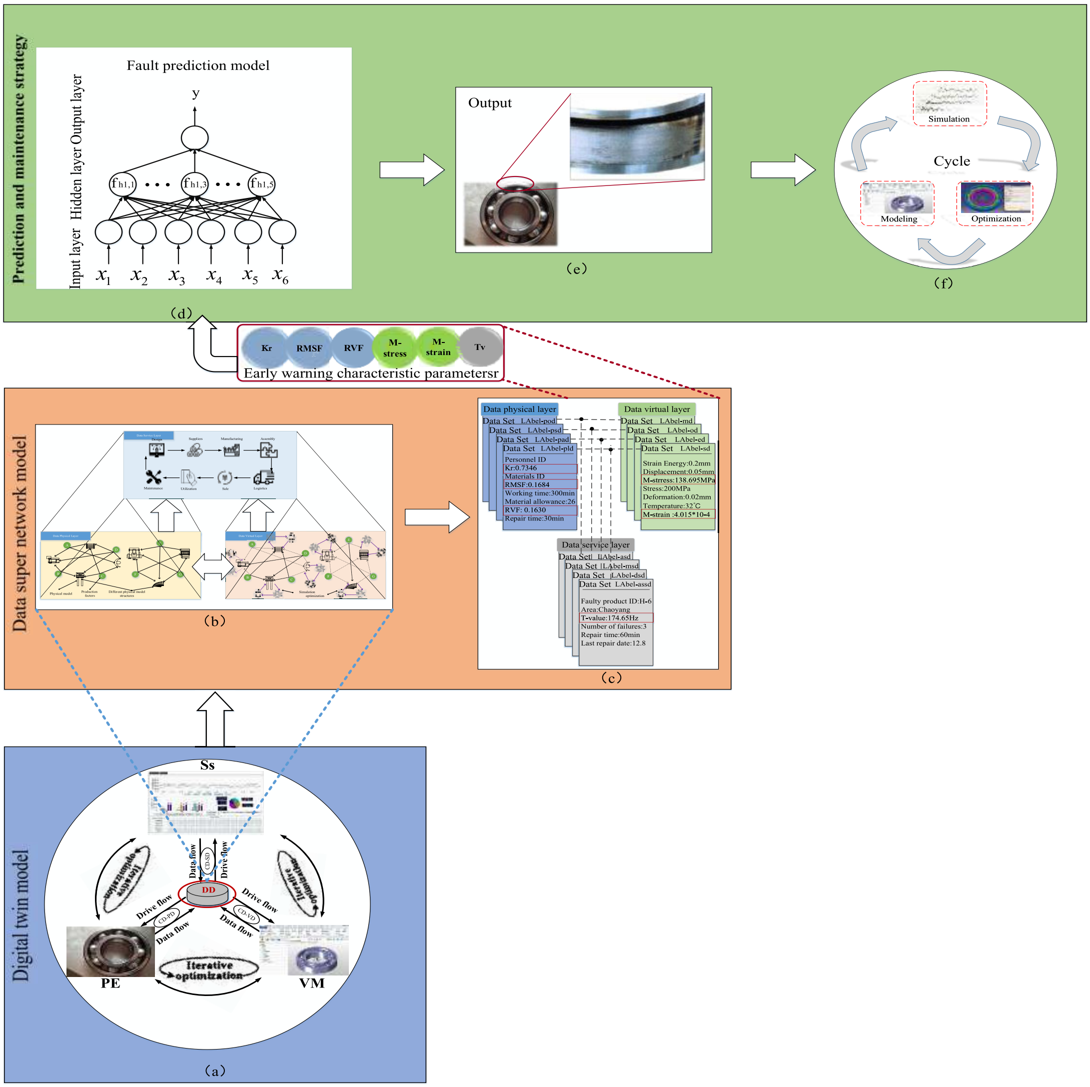


FIGURE 6. Fault prediction and maintenance strategy.

this algorithm, as shown in Fig.6(d). Finally, fault prediction model and input parameters are used to output fault causes, as shown in Fig.6(e).

The data was used for the fault prediction model which comes from the database of a satellite control center. This paper select 1000 groups of data and their corresponding failure modes from the databases. In the process of verification, 800 data points are selected from 1000 data signals and corresponding fault modes (e.g. Health status, out-race fault, inner-race fault and rolling ball fault) as training data, while the remaining 200 groups of data were used as test data. Among them, 800 training data sets include four different failure modes, each with 200 sets of data. The remaining 200 data sample test sets also include four different failure modes, each with 50 pairs of data. According to the method of this paper and the traditional method, four sets of training data are input into the prediction model, for training. The output of failure mode is as follows: health state (0,0,0), rolling ball fault (l,0,0), out-race fault (0,l,0), inner-race fault (0,0,l). The training data are shown in Table 1. After the training is completed, the sample test set data is used for verification. The test output is shown in Table 2.

According to the MATLAB simulation of 1000 sets of data, the iteration speed and iteration error of the model under different methods can be obtained. In this paper, three kinds of input-output data are used to train the fault prediction model respectively: the traditional method, the method in this paper without preprocessing process, and the method in this paper after the preprocessing process. The specific results are as follows.

This paper select two groups of data in the three-layer data super-network that reflect more representative features of faults, the accuracy is higher, as shown in Fig. 7(B) and Fig. 7(C). Compared with Fig. 7 (A) and Fig. 7 (C), the simulation results show that for the same sample, the result of this method is better iteration error than the traditional

TABLE 1. Test experimental data (section).

Number	Kr	RMSF	RVF	Max stress /MPa	Max strain $*10^{-4}$	Theoretical value /Hz	Failure mode
1	0.0013	0.9607	0.9312	101.242	3.221	186.72	(0,0,0)
2	0.9287	0.8370	0.5952	60.236	7.125	231.24	(1,0,0)
3	0.9447	0.8259	0.4561	62.879	6.984	107.84	(1,0,0)
4	0.7753	0.1984	0.1520	133.642	3.831	174.81	(0,1,0)
5	0.6668	0.1233	0.1543	137.534	4.012	123.05	(0,1,0)
6	0.1623	0.0632	0.0763	39.826	9.724	234.87	(0,0,1)
7	0.1492	0.0877	0.0685	43.558	9.915	178.73	(0,0,1)

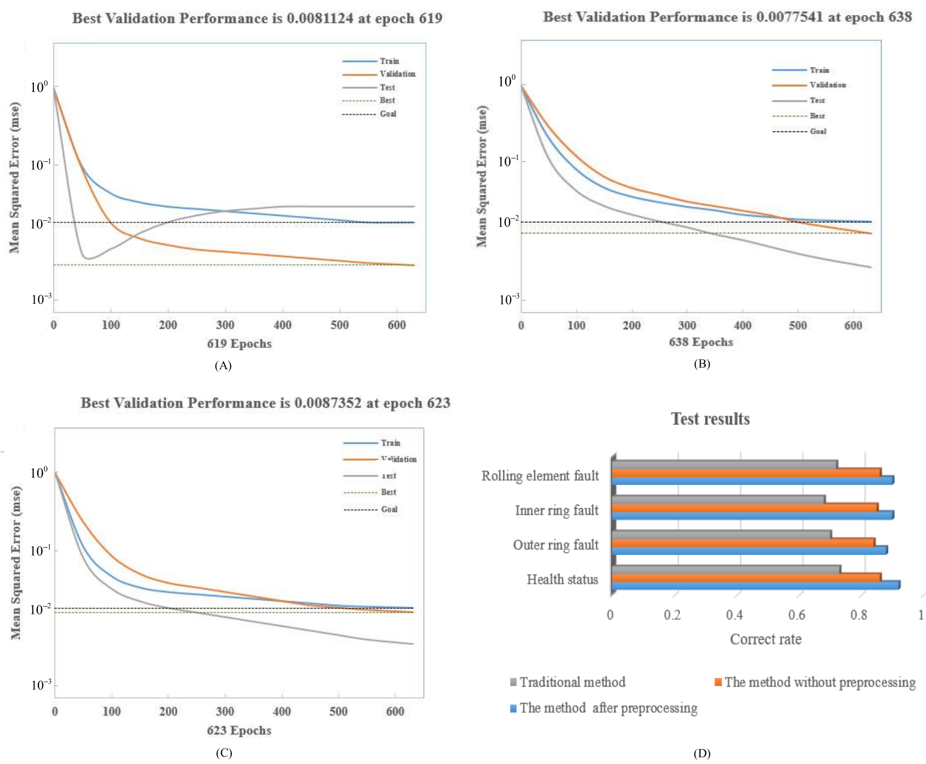


FIGURE 7. Fault prediction results.

method when the iteration speed is similar. Compared with Fig. 7(B) and Fig. 7(C), the simulation results show that under the condition of similar iteration speed, the result of the method in this paper is better iteration error than without preprocessing. The accuracy rate of test results in Fig. 7(D) shows that the prediction accuracy rate of the method in this paper after preprocessing is higher than the method in this paper without preprocessing and the traditional method. Therefore, this method is effective and efficiency in aerospace bearing fault prediction.

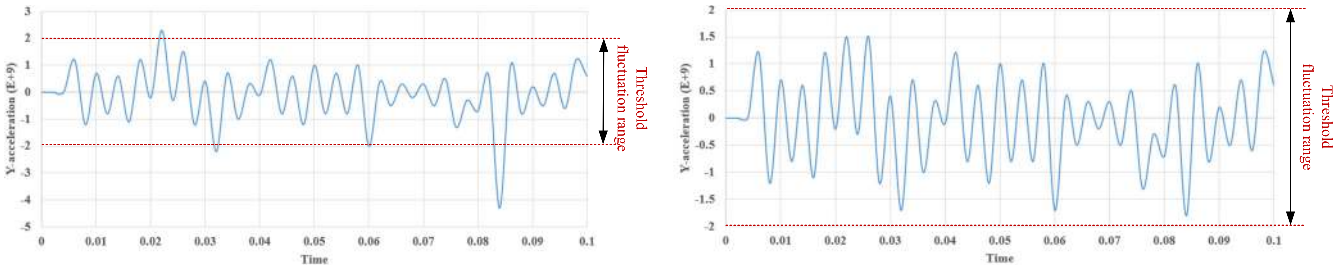
C. FAULT MAINTENANCE STRATEGY

As shown in Fig. 6(e), the prediction result of bearing failure in the experiment is out-race wear, and the amount of wear is small. According to the result of this fault prediction, it is necessary to carry out brush-plating repair process for this fault. This maintenance process is shown in Fig.6(f).

① According to the wear position of the outer-ring of the bearing, the working path of the electroplating pen is programmed in the virtual model, and the program is the maintenance process scheme.

② Before the physical model executes the program, the running program of the electroplating pen is verified in the virtual model. The virtual model restores the actual working environment. Then, the electroplating pen executes the program to repair.

③ After the electroplating pen is repaired in the virtual model, the bearing is put in the virtual model to actual working. Researchers observe the fluctuation value and fluctuation threshold of the vibration acceleration curve of the repaired part in the Y-direction for a period of time. If the fluctuation



(A)
(B)

FIGURE 8. Vibration curve of fault location.

TABLE 2. Test set data output (section).

Number	Kr	RMSF	RVF	Max stress/MPa	Max strain $*10^{-4}$	Theoretical value /Hz	Failure mode	Prediction Results of Traditional Methods	The prediction results of this method
1	0.0056	0.9837	0.9264	105.128	3.011	189.62	(0, 0, 0)	Ture	Ture
2	0.9332	0.8430	0.6056	64.235	7.521	240.87	(1, 0, 0)	False	Ture
3	0.8991	0.8536	0.5466	65.231	7.215	108.21	(1, 0, 0)	Ture	Ture
4	0.7436	0.1684	0.1630	138.695	4.015	174.65	(0, 1, 0)	False	Ture
5	0.6769	0.1536	0.1585	136.842	3.952	142.35	(0, 1, 0)	False	Ture
6	0.1458	0.0721	0.0652	40.125	9.534	256.32	(0, 0, 1)	False	Ture
7	0.1685	0.0752	0.0542	46.256	10.523	167.21	(0, 0, 1)	Ture	False

value of the vibration acceleration curve is found to exceed the fluctuation threshold value, this means that the fault is poorly maintained, as shown in Fig. 8 (A). Threshold is the range of maximum and minimum fluctuation when the fault part works normally for several times. At this time, the electroplating pen program is optimized again until the fluctuation value does not exceed the threshold value, as shown in Fig. 8(B). The optimization process is completed by using the trajectory optimization algorithm embedded in the digital twin service layer.

④ The optimized maintenance process scheme is transmitted to the physical model for execution.

VI. CONCLUSION

When mechanical products work in complex environment, they are faced with problems, such as unreliable prediction of product failure, precise location of fault and unreasonable construction of optimal maintenance strategy, which reduces the stability and life of the project at hand. Based on digital twinning technology, this paper proposes a ''super-network-warning features'' fault prediction and maintenance method. Specifically: 1) In order to quantitatively study the interaction among heterogeneous agents in the digital twin model. A three-layer super-network model of data is constructed, based on digital twin five-dimensional structure, which provides a classified data resource pool for distributed data resources. 2) Through the process of data collection and preprocessing, the early-warning-features in different data super-network layers are selected as the input parameters of the prediction model, and the fault causes can be accurately predicted. At the same time, according to the simulation and optimization function of the virtual model in digital twinning, a real-time maintenance strategy is formulated for the fault causes. This method has realized the effective combination of fault prediction and maintenance. 3) Taking an aero-engine bearing as an example, this method is compared with the traditional method. The results show that the model prediction error of this method is better than the traditional method when the convergence rate is similar. At present, this research is still in the initial stage, and the matching algorithm is not perfect and cannot be applied on a large scale. Future research work will mainly focus on the following two aspects: 1) According to the deep-level data characteristics of digital twins, perfect the data model of three-layer super-network. 2) Develop algorithms which are more suitable for model operation.

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ZHIFENG LIU received the Ph.D. degree in mechanical design from the Mechanical Engineering and Automation College, Northeastern University, in 2001.

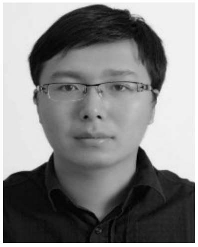
He is currently an Associate Dean of the College of Mechanical Engineering and Applied Electronics Technology, Beijing University of Technology, and the Director of the Beijing Key Laboratory of Advanced Manufacturing Technology. His research interests include digital design and manufacturing, manufacturing services, and manufacturing system information.

WEI CHEN received the B.S. degree in mechanical engineering from the Shandong JiaoTong University of China, in 2017. He is currently pursuing the master's degree in mechanical engineering with the Beijing University of Technology.

His research interests include digital twin, digital design, and smart manufacturing.

CAIXIA ZHANG received the Ph.D. degree in engineering from the Mechanical Engineering College, Tsinghua University, in 2015.

She is selected as the Innovation talents and Outstanding talents of the Beijing University of Technology. She focuses on the fields of harmonic drive in robot, manufacturing service management, and sustainable manufacturing. She received the First Prize of Beijing Science and Technology Progress Award, in 2018.



CONGBIN YANG received the Ph.D. degree in man-machine and environmental engineering from the Beijing Institute of Technology, in 2015.

He is currently a Research Fellow with the Beijing Key Laboratory of Advanced Manufacturing Technology, Beijing University of Technology. He has hosted and participated multiple research projects over the past three years. His researches focus on control technology for tracked vehicles and structural dynamic coupling properties, and intelligent manufacturing.

HONGYAN CHU received the bachelor's and master's degrees in engineering from Jilin University, in 1994 and 1997, respectively, and the Ph.D. degree in mechanical design and theory from the Beijing University of Technology, in 2013.

She is currently the Dean of the Department of Mechanical Manufacturing and Automation, College of Mechanical Engineering and Applied Electronics Technology, Beijing University of Technology. Her research interests include intelligent manufacturing research, process simulation, and optimization research of hot machining process and digital design.