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Review

Application of Life Cycle of Aeroengine Mainshaft Bearing Based on Digital Twin

Yunfeng Li [1,2,*], Ming Li [2], Zhong Yan [3], Ruoxuan Li [2], Ao Tian [2], Xinming Xu [2] and Hang Zhang [2]

[1] Key Laboratory of Advanced Manufacturing Intelligent Technology of Ministry of Education, Harbin University of Science and Technology, Harbin 150080, China
[2] School of Mechanical and Power Engineering, Harbin University of Science and Technology, Harbin 150080, China; landl0825@hotmail.com (M.L.); lrxhtyx@hotmail.com (R.L.); ta1314521ta@outlook.com (A.T.); xuxinming-@hotmail.com (X.X.); hangzhang00@outlook.com (H.Z.)
[3] AECC Harbin Bearing Co., Ltd., Harbin 150500, China; yanzongzi7679048@163.com
* Correspondence: yunfengli@hrbust.edu.cn; Tel.: +86-186-4602-9989

Abstract: Aeroengine mainshaft bearings are key components in modern aeroengines, and their main functions are to support the rotation of the main shaft of the aeroengine in harsh environments, such as high temperature, heavy load, high speed and oil break; reduce the friction coefficient during the high-speed rotation of the main shaft; and reliably ensure the rotation accuracy and power transmission of the aeroengine's main shaft during operation. The manufacture of aeroengine mainshaft bearings requires complex processes and precise machining to ensure high performance and reliability, and how to intelligently complete the production and manufacture of mainshaft bearings and ensure the strength and accuracy of the bearings, quickly distinguish the fault types of the bearings and efficiently calculate, analyze and predict the life of the bearings are the current research hotspots. Therefore, building a high-fidelity and computationally efficient digital twin life cycle of aeroengine mainshaft bearings is a valuable solution. This paper summarizes the key manufacturing technology, manufacturing mode and manufacturing process based on digital twins in the life cycle of aeroengine mainshaft bearings, including the metallurgical process, heat treatment process and grinding process of aeroengine mainshaft bearings. It presents a fault diagnosis and life analysis of mainshaft bearings of aeroengines, discussing the key technologies and research directions of the life cycle of mainshaft bearings based on digital twins.

Keywords: aeroengine mainshaft bearing; digital twin; metallurgical process; heat treatment process; grinding process; fault diagnosis; life prediction

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1. Introduction

Bearings are one of the most important parts in the mechanical field, from the ball bearings used in bicycles in the early days to the mainshaft bearings of aeroengines, the development of bearings also directly reflects the development level of modern industry [1]. Improving the production and processing links of aeroengine mainshaft bearings (hereinafter referred to as mainshaft bearings) and improving the service life of mainshaft bearings are hot topics in the aviation field, and they are also the development direction of bearings in modern industry. Due to the differences in the tolerance level, technical requirements, materials and batches of aeroengine mainshaft bearings, the basic production process is not the same. Among them, metallurgy, heat treatment and grinding are the most critical. At the same time, to improve the life and reliability of the mainshaft bearing, it is also necessary to carry out a lot of work on the fault diagnosis and life analysis of the mainshaft bearing. With the continuous improvement of bearing manufacturing technology, such as new materials [2], process levels, machining accuracy and structural optimization, each part of the technological improvement directly affects the service life of the final bearing. Traditional research methods usually have the problems of a large amount of calculation, inability to be controlled online and high test costs. The arrival of the information age has solved these problems. However, the current information of each link in the life cycle of aeroengine mainshaft bearings cannot be interacted with well, and there is information asymmetry in its design, manufacturing and control systems, which will lead to rework and errors. This will ultimately affect the quality and life of the mainshaft bearing. Digital twins have been applied by scholars in the manufacture and fault diagnosis of bearings, some scholars have established manufacturing systems and fault diagnosis methods based on digital twins, and have achieved corresponding results. For example, Cao Hongrui invented the bearing modeling and model updating method based on digital twins [3], the bearing performance degradation evaluation method [4], the aeroengine mainshaft bearing damage detection method based on digital twins [5] and the remaining life prediction method [6]. Zhao Yanling invented the bearing life cycle monitoring method based on digital twins [7], and Guo Liang invented the rolling bearing life cycle condition monitoring method [8]. Therefore, the establishment of a digital twin platform is an important way to support the efficient computational design and to construct parallel control optimization algorithms [9].

2. The Development and Significance of Digital Twins

The concept of the digital twin was first proposed in 2003 by Grieves, a professor at the University of Michigan [10], as shown in Figure 1. Due to the limited information collected at that time, most of which was paper information, the concept of the digital twin could not be further perfected. With the development of information technology and continuous improvements in the level of industry, the concept of the digital twin has gradually become known. Furthermore, with the proposal of Industry 4.0, they have become one of the important technologies of intelligent manufacturing.

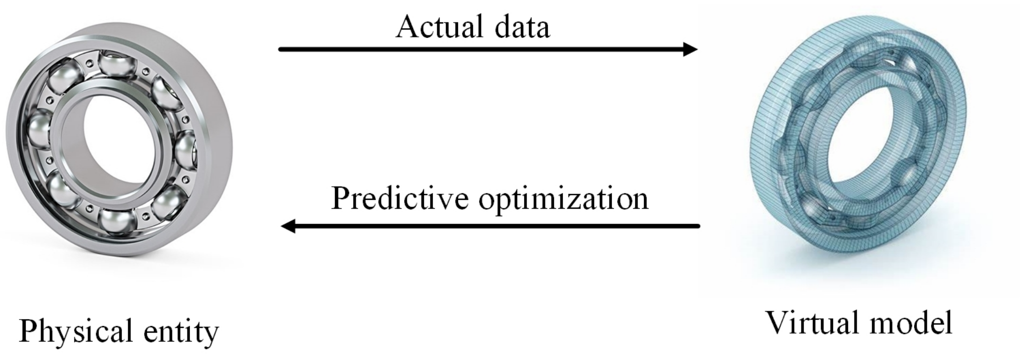

Figure 1. Digital twin model.

Digital twins involve digitally establishing virtual entities from physical entities in the real world, and then connecting physical entities with virtual entities through data and integrating data, including information technologies, such as big data, cloud computing and sensors, to achieve intelligent services [11]. The virtual model is established based on the data of the physical entities in the real world, such as the requirements of dimensions and tolerances in the industry and the temperature, humidity, climate and other factors in the environment. These data are provided to the virtual model to establish unique characteristic parameters, and then the virtual model is used to simulate the relevant data or real-time data that may occur or have occurred in reality. The data obtained by the simulation are then fed back to the physical entity to achieve the application of prediction and management to achieve efficient and intelligent services.

3. Manufacture of Aeroengine Mainshaft Bearing Based on Digital Twin

Manufacturing is a process of converting resources into products [12]. In the manufacturing process of aeroengine mainshaft bearings, the required materials, tools and other resources are planned, production plans for mainshaft bearings are designed, and the manufacturing process of mainshaft bearings by machining is pre-defined. Thereby, the efficiency of the mainshaft bearing manufacturing process is improved, the cost is reduced and the quality and stability of the mainshaft bearing are ensured.

3.1. Operation Mode of Digital Twin Shop Floor

To realize the manufacture of aeroengine mainshaft bearings, the shop floor is the most basic executor, which provides resources and organizes these resources in an orderly manner to produce mainshaft bearings. From the perspective of the development of the shop floor, the initial physical space, the current information space and the physical space begin to interact, so the production capacity of the shop floor is strengthened [13]. However, the data of the physical shop floor and the virtual shop floor lack integration and interaction, and there are unexpected uncertainties in the physical shop floor, so it is difficult to accurately control the actual manufacturing process of the physical shop floor according to the proposed manufacturing process of the virtual shop floor. To solve the above problems, the intelligent shop floor of intelligent manufacturing based on digital twins is a new manufacturing mode with real-time information interaction and is a form of sustainable green manufacturing. Tao Fei [14] proposed a new manufacturing model based on digital twin and digital twin shop floor (DTS), namely the digital twin five-dimensional model, as shown in Figure 2. The digital twin shop floor is composed of a physical shop floor (PS), virtual shop floor (VS), shop floor service system (SSS) and shop floor digital twin data (SDTD). The physical shop floor exists objectively, and the virtual shop floor is the digital mapping of the physical shop floor. The shop floor service system provides support and service for the manufacturing process. The shop floor digital twin data are the data obtained by the fusion of all relevant data of the physical shop floor, virtual shop floor and service system, which provide power for the data twin shop floor. The digital twin shop floor can also be applied to the health management of the shop floor equipment, monitoring the performance of the equipment, locating the cause of the fault and formulating the maintenance strategy in time [15]. The value and potential of the concept of a virtual factory based on digital twins have been explored in the field of manufacturing engineering [16].

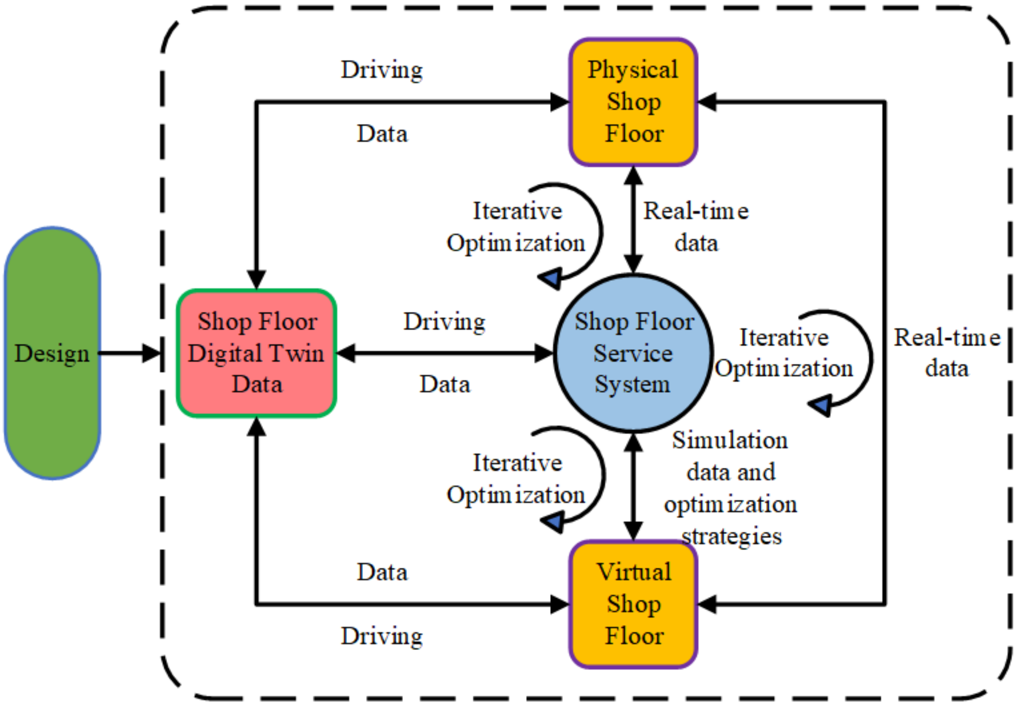

Figure 2. The composition and operation mechanism of the digital twin shop floor.

To study the operation mechanism of the digital twin shop floor, the detailed process of executing the production task is given. When the physical shop floor needs to complete the production task of aeroengine mainshaft bearings, the shop floor digital twin data (SDTD) fuse all relevant data, such as the equipment data of the physical shop floor (PS), the simulation data of the virtual shop floor (VS) and the enterprise data and historical data of the shop floor service system (SSS), to generate equipment and materials that meet the tasks, tools and human resources allocation plans. Based on the distribution plan, the shop floor service system (SSS) generates a production plan for the actual manufacturing process of the mainshaft bearings. After the plan is simulated by the virtual shop floor (VS), the data are fed back to the shop floor service system (SSS), the data are corrected and optimized, and finally a suitable production plan is obtained. The physical shop floor (PS) completes the manufacturing process of the mainshaft bearings in strict accordance with the production plan, and the manufacturing process will transmit real-time data to the virtual shop floor (VS) to ensure consistency between the physical shop floor (PS) and the shop floor service system (SSS). This optimizes and ensures the accuracy of the control of the production process of the mainshaft bearings.

3.2. Metallurgical Process of Bearing Steel Based on Digital Twin

Many factors affect the service life of aeroengine mainshaft bearings, and the quality of bearing steel is one of the key factors. In the production process of bearing steel, the content and size of different types of inclusions in the refining process are controlled to control the cleanliness of molten steel in the refining of bearing steel, thereby controlling the quality of bearing steel bars [17]. The refining process of bearing steel is optimized by reducing the content of impurity elements, reducing the size of inclusions and controlling the shape and distribution of inclusions in the steel. For example, the oxygen content in GCr15 bearing steel is closely related to the fatigue life of the steel, and the oxygen content of some high-end bearings is below 0.0005% [18]. In addition, different metallurgical heats will affect the material composition of bearing steel, and the fluctuation in composition will lead to changes in the process performance and service performance of bearing steel, which in turn leads to quality fluctuations in subsequent processes [19].

For the high-precision control of steel properties, the State Key Laboratory of Rolling and Automation (RAL) established research on the prediction model of high-fidelity material structure and properties under the background of big data [20].

The system mechanism shown in Figure 3 is based on the actual hot-rolling production line and establishes a model of the relationship between microstructure evolution and microstructure properties during hot continuous rolling and continuous cooling. The parameters in the model are optimized by using a big data drive and intelligent algorithms, enabling the development of high-fidelity physical metallurgy models. In addition, a big-data-driven machine learning hot-rolling process optimization system has been developed, which can perform high-precision online prediction of the mechanical properties of materials and obtain high-precision and high-fidelity prediction models. Compared with the fluctuation in the mechanical properties of HP195 steel, the optimization process based on the prediction model greatly improves the accuracy of yield–strength ratio control compared with the traditional process.

3.3. Heat Treatment Process of Bearing Steel Based on Digital Twin

Aeroengine mainshaft bearings need to work in harsh environments, such as high temperature, heavy load and high speed, which require bearing steel to achieve fatigue resistance, wear resistance, high strength, good stability and corrosion resistance [21]. Therefore, a good internal structure of the bearing steel can not only achieve performance in the above-mentioned conditions but also ensure that the core has good fracture toughness and strength.

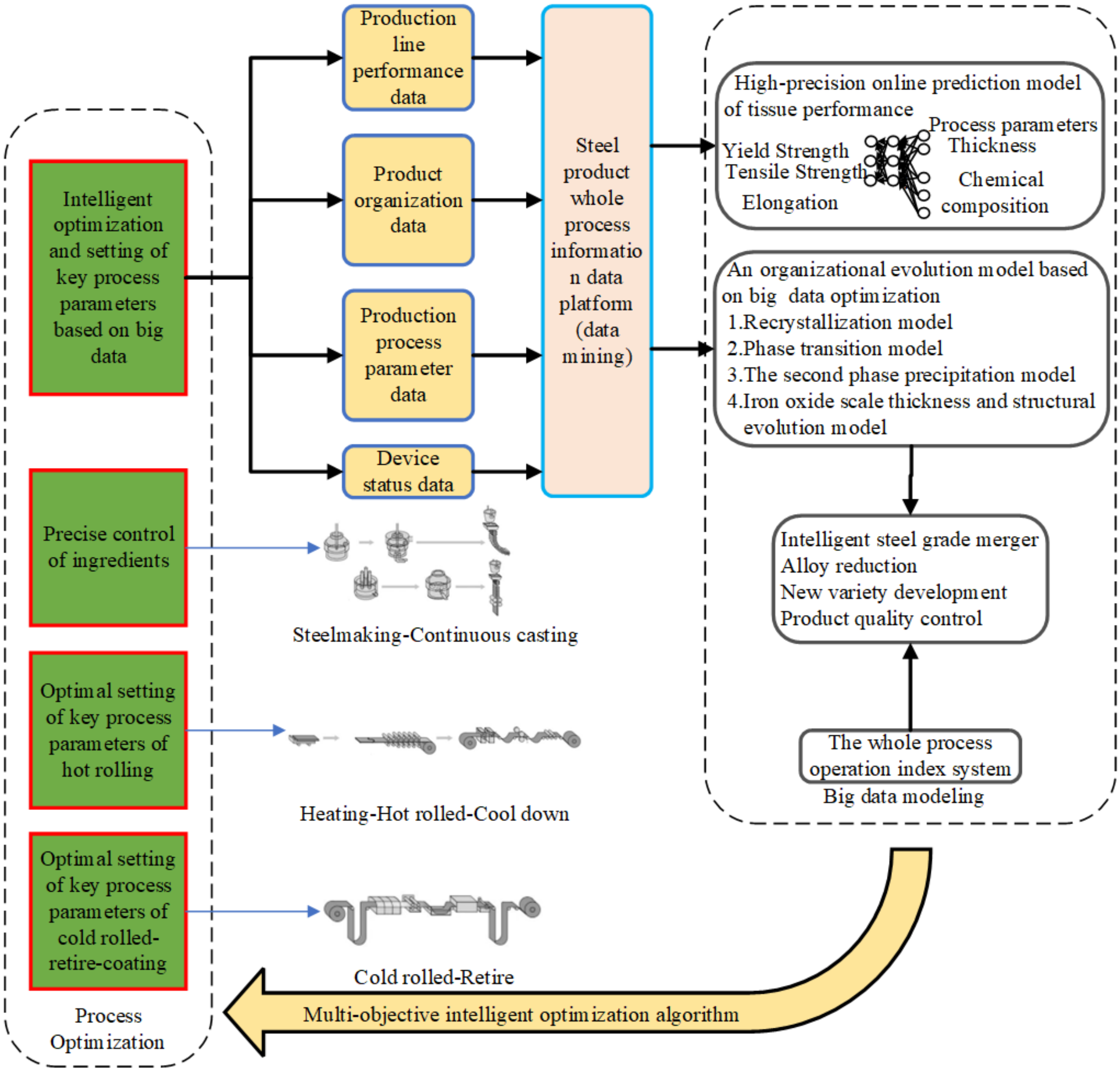

Figure 3. Microstructure property prediction and optimization of hot-rolled steels.

Taking GCr15 high-carbon chromium bearing steel as an example [22], the conventional heat treatment process involves tempering after quenching, and the microstructure after martensite quenching is composed of martensite-retained austenite and carbides. Tempering immediately after quenching eliminates internal stress, improves toughness and stabilizes structure and size. For bearing parts that require high dimensional accuracy, it is generally desirable to have as little retained austenite as possible. However, retained austenite can improve the toughness and crack growth ability. Under certain conditions, the retained austenite on the surface of the workpiece can also reduce the concentration of contact stress and improve the contact fatigue life of the bearing. Therefore, an appropriate amount of retained austenite is beneficial to improve the contact fatigue life and toughness of the bearing. Additionally, modern heat treatment processes, such as deep cryogenic treatment [23], austempering [24] and compound treatment quenching [25], can significantly change the microstructure in bearing steel to obtain good performance and toughness. The essence of bearing steel heat treatment is to control its microstructure by controlling the temperature change process of bearing steel. For example, the transformation rate of inclusions is affected by temperature [26], and the variation in holding time is related to the decarburization of bearing steel [27]. Therefore, the precise measurement and control of temperature are key to ensuring the quality of heat treatment of bearing steel.

To accurately measure and control the temperature during heat treatment, Dou Ruifeng [28] proposed the application of digital twin technology in heat treatment and a heat treatment model based on digital twins at the China Industrial Furnace and Metallurgical Industry Thermal Technology Development Conference (Figure 4). Based on big data and intelligent algorithms, Dou Ruifeng has established a radiation heat transfer simulation model suitable for 3D arbitrary space, which can accurately calculate the radiation heat transfer angle coefficient of 3D arbitrary space. Finally, after several experimental cases, it was verified that the actual annealing time of the heat treatment process optimized by the mathematical simulation model was reduced by 15%, the quality remained unchanged and finally the energy consumption and material consumption could be reduced and the production efficiency could be improved.

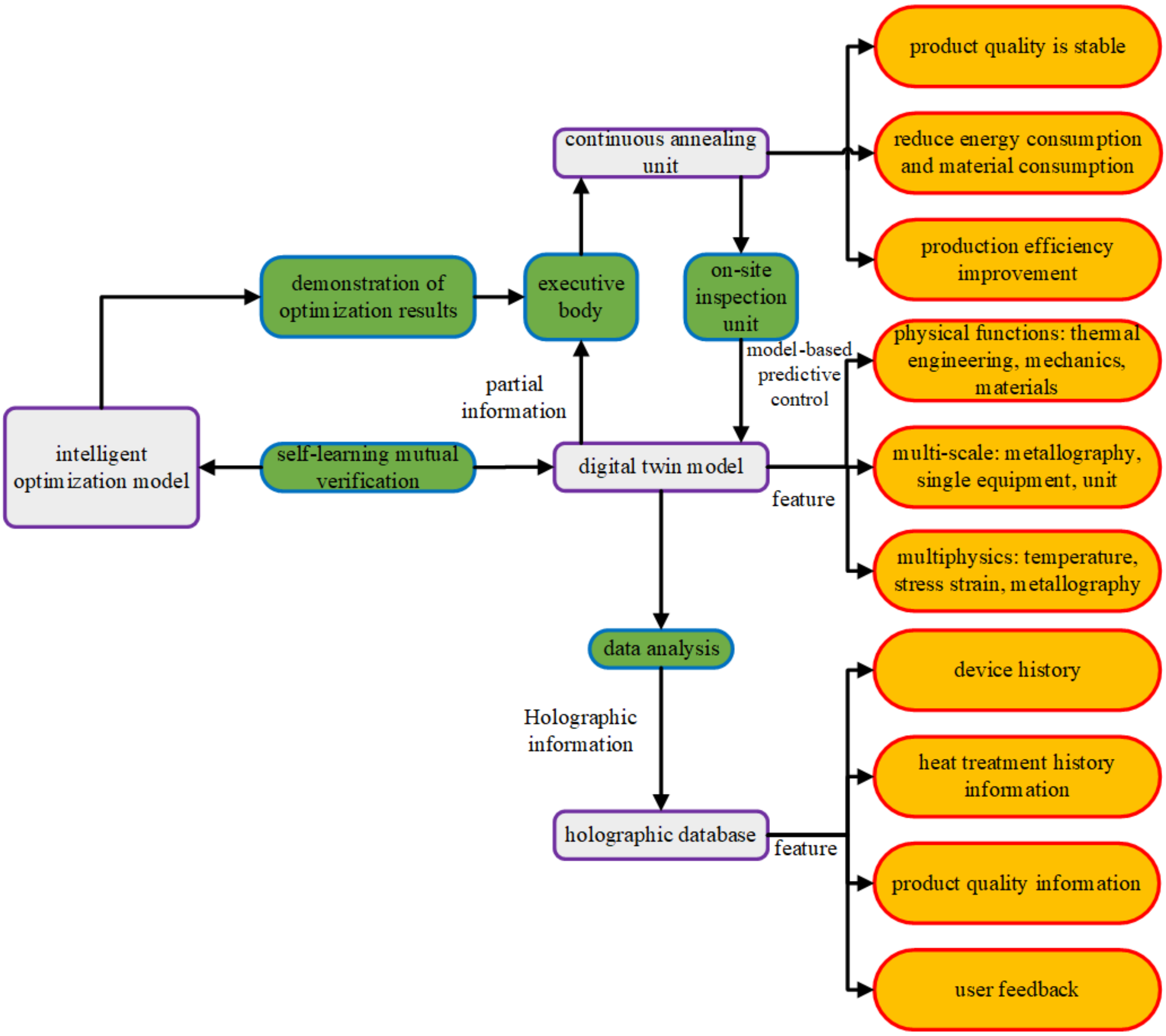

Figure 4. Heat treatment model based on digital twin.

A. I. Rudskoy [29] created a digital twin of the thermomechanical treatment (TMT) technique to describe the changes in the structural formation and properties of steels during heat treatment. Therefore, by using the calculation based on the digital twin heat treatment model, the process and chemical composition of different steels can be calculated so that a reasonable choice can be made during the heat treatment process to ensure a good organizational structure in the bearing steel.

3.4. The Mainshaft Bearing Grinding Technology Based on Digital Twin

In the production process of aeroengine mainshaft bearings, the cutting process and grinding process are indispensable. The the grinding process system is the unity of the grinding machine, the tool, the fixture and the workpiece, and the quality of its dynamic performance directly affects the quality of the processed workpiece [30]. The grinding process is the most complicated in the processing of mainshaft bearings. This complexity is reflected in more performance indicators and higher precision is required; the processing and forming mechanism is more complex, there are many factors affecting the processing accuracy and the online detection of processing parameters is difficult [31]. For example, the mainshaft bearing ring will generate a lot of grinding heat during the grinding process. Most of the heat generated by the grinding process is transferred to the workpiece, which brings certain thermal damage to the machined surface of the workpiece, resulting in a decrease in the hardness of the surface layer. Cracks and grinding burns are the most common surface defects in bearing processing. Grinding burns cause the deterioration of the bearing surface's organization, which accelerates the fatigue and wear of the mainshaft bearing during the working process and seriously affects the service life of the mainshaft bearing [32]. Sun Xufeng believes that by combining ultra-precision cutting with ultra-high-speed cutting, increasing the cutting speed and appropriately increasing the strength and hardness of soft materials in ultra-precision cutting, machinability can be improved and surface and sub-surface damage can be reduced [33].

The grinding process is the most commonly used finishing method for precision bearings. It is the final process that must be carried out for precision bearings, which can reduce surface roughness and ensure matching dimensional accuracy. For example, grinding is required in places where materials such as rings, spheres and raceways of the mainshaft bearings are difficult to machine and require high precision and low surface roughness [34]. Therefore, in terms of the production process of aeroengine mainshaft bearings, the technology of ultra-precision machining directly affects the quality of the mainshaft bearings.

The quality of the grinding wheel plays a vital role in the grinding process. Amr Monier [35] established a mathematical model of the grinding wheel and the workpiece and verified through experiments that the predicted surface of the mathematical model has good compatibility with the machined surface, which affects the grinding accuracy of the structural surface. Real-time event-based digital twin applications can provide support for users and decision-making processes. High-fidelity virtual models can simulate and predict the state and behavior of physical entities, and provide real-time feedback to users. The digital twin real-time event-based platform can automatically optimize physical entities where possible [36]. Therefore, the grinding wheel digital twin [37] (Figure 5) can clearly describe the energy and resource efficiency of the sustainable grinding process. Users can view the information of the grinding wheel by logging into the website page, allowing each individual in the manufacturing hierarchy to access and share the information, and can also provide technical support and product services for the maintenance line and provide users with maintenance and improvement suggestions according to the status of the grinding wheel, increasing energy and resource efficiency.

The grinding process of modern mainshaft bearings is completed by CNC (Computer Numerical Control) machine tools. To achieve mass production, it is necessary to continuously experiment to formulate optimal path planning for CNC machine tools. During the experiment, due to the influence of parameters such as grinding force and grinding temperature, the bearing rings produced by the same procedure may be unstable in accuracy and roughness. The digital twin model of a grinding system established by Liu Hongbin [38] can effectively predict the grinding force. Yong Zheng [39] established an improved cylindrical wet grinding temperature (ICWGT) model considering the lubrication effect of the grinding fluid and believed that the proposed model could more accurately predict the workpiece grinding temperature compared with a method that does not consider the lubrication effect. Pavel P. Pereverzev [40] proposed a dynamic programming method (DPM) for the design of circular grinding automatic cycle optimization based on digital twin technology synthesis, as shown in Figure 6. The optimal trajectory of the radial feed change cycle is calculated to design the optimal grinding cycle and the automatic grinding cycle method is designed with the optimal cutting condition parameters for the CNC machine tool. It can ensure the stable quality of the machined surface in terms of precision, roughness and hardness when processing a batch of parts under different conditions, and improves the quality and reliability of the CNC machine tool control program.

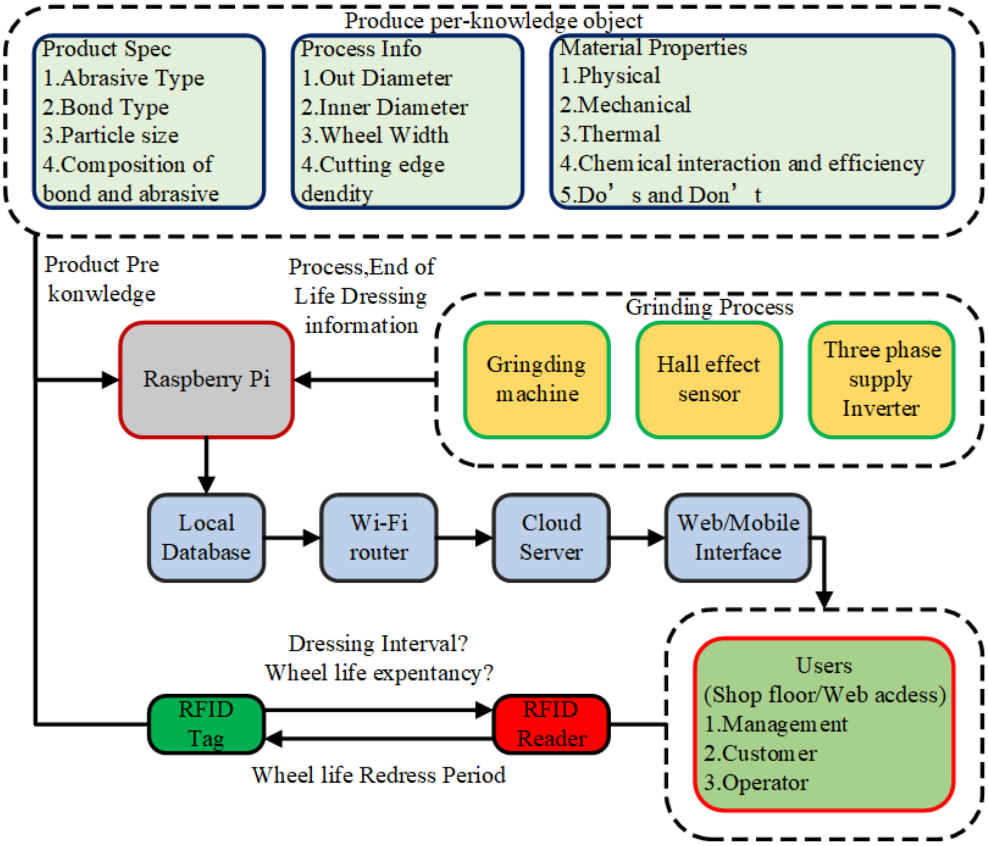

Figure 5. Heat treatment model based on digital twin.

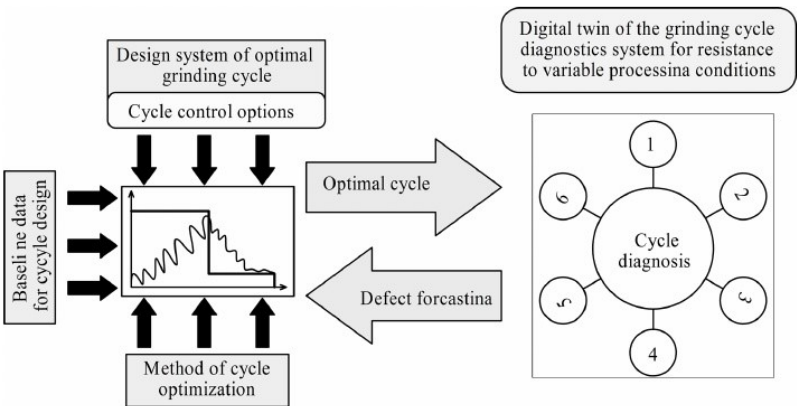

Figure 6. Scheme of the interaction of the system for optimizing the DPM cycle with the digital twin of the cycle testing system [40].

The working principle of the program optimization method proposed by Shen Nanyan [41] based on the mapping capability of the actual working conditions of the digital twin system is shown in Figure 7. The program optimization module of the application layer of the digital twin system obtains equipment data and workpiece data through the data layer and then generates model parameters according to the state data of the grinding wheel during the grinding process. When the workpiece or grinding center configuration changes, the digital twin system can sense the changed data and then update the optimization model parameters. In addition, the root mean square value of the acoustic emission signal is extracted and analyzed during the grinding process to evaluate the condition of the grinding wheel. Finally, through example analysis, it is verified that the optimization method has a good dynamic response to the change in working conditions, and the composite model for the rotating workpiece can accurately describe the actual composite grinding process.

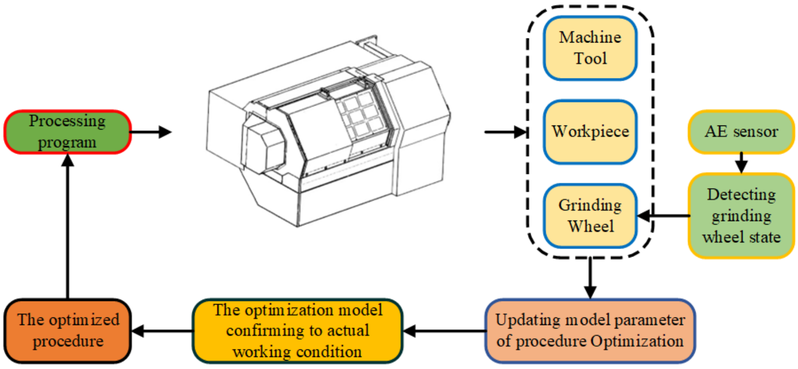

Figure 7. Schematic diagram of procedure optimization based on the DT system.

The grinding process based on digital twins can integrate the complexity of grinding motion, machining characteristics, the diversity of available grinding wheels and changes in working conditions to quickly program a safe and efficient compound grinding program and solve the problem of program optimization in the grinding process.

Synthesizing the shop floor operation mode, metallurgy, heat treatment process and grinding process in the above-mentioned manufacture of digital-twin-based aeroengine mainshaft bearings clearly expresses the relationship between the physical entity, virtual model and database in each part. The digital twin manufacturing process diagram of the aeroengine mainshaft bearing is given, as shown in Figure 8.

Based on the same database for the workshop operation mode, metallurgy, heat treatment process and grinding process based on a digital twin, the virtual model fully reflects the entire cycle of the manufacturing process of the mainshaft bearing of the aeroengine. Researchers can complete the production control of the mainshaft bearing online, or refer to the data of each manufacturing link in the digital twin database and the differences between each manufacturing link, and design the structure and bearing type of the mainshaft bearing according to the needs of different aeroengines. It is also possible to design the manufacturing mode of the mainshaft bearing and the process flow of each link online according to the structure of the designed mainshaft bearing. The online design of the manufacturing process of the mainshaft bearing of the aeroengine based on digital twinning requires a lot of calculations, and cloud computing can fully support researchers to design the manufacturing process of the mainshaft bearing online based on the digital twin. The production process of the mainshaft bearing can be monitored at any time and anywhere, and the problems in the production process can be found and solved in time. The digital twin manufacturing process of the aeroengine mainshaft bearing should realize the accurate control of the manufacture of spindle bearings in a digital way, reduce the quality fluctuation in the mainshaft bearing in different batches, reduce the inclusion content in the bearing and finally improve the fatigue life of the mainshaft bearing.

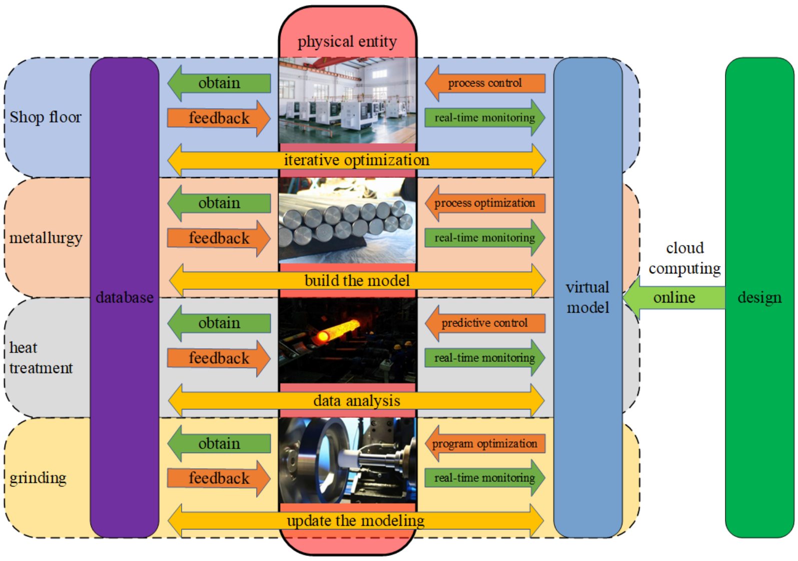

Figure 8. Digital twin manufacturing process of aeroengine mainshaft bearings.

4. Fault Diagnosis and Life Analysis of Aeroengine Mainshaft Bearings Based on Digital Twin

Aeroengine mainshaft bearings work for a long time under high temperature, heavy load and high speed, and the balls or inner and outer ring raceways of the mainshaft bearing will inevitably have failures such as fracture, wear, gluing, fatigue shedding, plastic deformation and other failures. If the mainshaft bearing cannot be maintained and treated in time, the fault may spread, be amplified and have a chain reaction, which will affect the normal work of the equipment and even cause the equipment to stop and even explode in serious cases [42]. At present, the fault mechanism of the mainshaft bearing mainly extracts features from the vibration signal. The vibration data of the rolling bearing collected by the sensor cannot be directly used for manual identification. Therefore, the data of the bearing are processed by data processing technology after collection, so that the characteristics of the obtained bearing are easy to manually identify [43]. To further judge the performance degradation of the mainshaft bearing, a multi-parameter method is used to extract the parameters of the mainshaft bearing, such as lubricating fluid flow [44], oil wear particle monitoring [45], the bearing's inner and outer ring temperature [46] and other signal features. Based on the collected signal characteristics, the fault category can be effectively identified and the reliability of the mainshaft bearing can be judged. The monitoring data of aeroengine mainshaft bearings under working conditions are collected by various sensors, but the working environment of the mainshaft bearing is relatively harsh and many performance data cannot be easily measured during operation [47]. Fang Xin [48] believes that the key sensor technology for future digital twins is to integrate multi-purpose sensors into one sensor. Not only can the cost of the sensor be reduced, but also the stability and reliability of the sensor in the monitoring process can be increased. Therefore, the digital twin technology improves the data accuracy in the fault signal of the mainshaft bearing, and the accuracy of the data will also affect the accuracy of the mainshaft bearing fault diagnosis.

4.1. Fault Diagnosis of the Mainshaft Bearing Based on Digital Twin

To reduce the length of the data and ensure the accuracy of the data as much as possible, modern researchers use algorithms to process the original data and extract fault characteristics. Jianhua Yang [49] proposed an improved EMD method—the combination of ensemble empirical mode decomposition (EEMD) and adaptive stochastic resonance (SR)—which can decompose useful information that characterizes bearing faults into a single intrinsic mode function (IMF). It is used for the bearing fault feature extraction of different fault forms, and IMF has good anti-noise performance and stability. Huan Huang [50] used the Instantaneous Fault Characteristic Frequency and the Instantaneous Shaft Rotational Frequency (IFCF and ISRF) search algorithms to process Oscillatory Behavior-based Signal Decomposition (OBSD) to extract bearing fault features from pollution signals and perform resampling-free and tachometer-free bearing fault diagnosis. Wang, Baiyang [51] proposed a bearing fault diagnosis method based on spectrogram information fusion and a convolutional neural network. A one-dimensional vibration signal was transformed by a short-time Fourier transform to obtain a two-dimensional characteristic map, and the fault characteristics in the picture were extracted by a convolution neural network to complete the bearing fault diagnosis. Lv, Defeng [52] proposed a rolling bearing fault intelligent diagnosis model based on a multi-scale convolutional neural network and decision fusion. The original vibration signal was normalized and matrixed to form gray image samples, and these samples were convolved with different convolution checks by the convolution neural network so that multi-scale samples could be obtained. The results of these samples were fused to obtain the fault diagnosis results of bearings.

On the other hand, different artificial neural network methods have been established based on convolutional neural networks (CNN) to identify bearing faults and improve the accuracy of fault diagnosis, such as MACCNN [53], ADCNN [54], MT-1DCNN [55], 1-D CNN [56], CNN-GRU [57], etc., or an intelligent fault diagnosis model (GL-mRMR-SVM) based on support vector machine (SVM) and feature fusion and feature selection [58], a support tensor machine (STM) [59], etc., to establish a new fault identification method to improve the accuracy of mainshaft bearing fault diagnosis. Wang Rui [60] proposed a deep convolutional neural network that combines residual blocks and channel attention mechanisms for bearing fault diagnosis. The channel attention mechanism was used to improve the recognition ability of the model, and the residual blocks improved the characteristics of deep convolutional neural networks and the extraction ability, and ultimately improved the accuracy of fault diagnosis.

Farzin Piltan [61] used the data collected by the acoustic emission sensor to propose a digital twin technology for AE signal modeling and estimation and used a machine learning algorithm (SVM) for crack type and size diagnosis (Figure 9). Then, an acoustic emission signal estimation method based on a strict feedback backstep observer, integral term, support vector regression and the fuzzy logic algorithm was proposed [62]. The effectiveness of the algorithm was verified with a bearing dataset containing normal states and seven fault levels [63]. The self-adaptive technology method in this paper used the support vector machine to classify the faults of the eight states of the bearing, and then used the support vector machine to classify the bearing fault signals of the 3 mm and 6 mm crack sizes in the seven fault levels of the bearing fault signals to carry out fault classification. The average accuracy of the algorithm for crack type diagnosis and crack size diagnosis for the acoustic emission signal of the bearing was 97.13% and 96.9%, respectively. The main advantages of this adaptive technique are its simplicity, reliability and high modeling accuracy.

Qin Yi [64] proposed a rolling bearing digital twin model driven by a combination of data models to predict the evolution law of faulty rolling bearings. Combining the measured data, bearing fault dynamic model and a neural network, a rolling bearing digital twin framework was constructed. An improved CycleGAN (Cycle-Consistent Adversarial Network) network with smooth cycle consistency loss was proposed [65]. Improving the CycleGAN network can reduce the gap between simulated and measured data, enabling high-fidelity virtual models mapped by physical entities. The dynamic model of the bearing failure and the virtual model mapped to the physical entity together constitute the digital twin model of the rolling bearing. The proposed digital twin model can effectively generate bearing vibration data with the same variation trend and fault characteristics as the actual data.

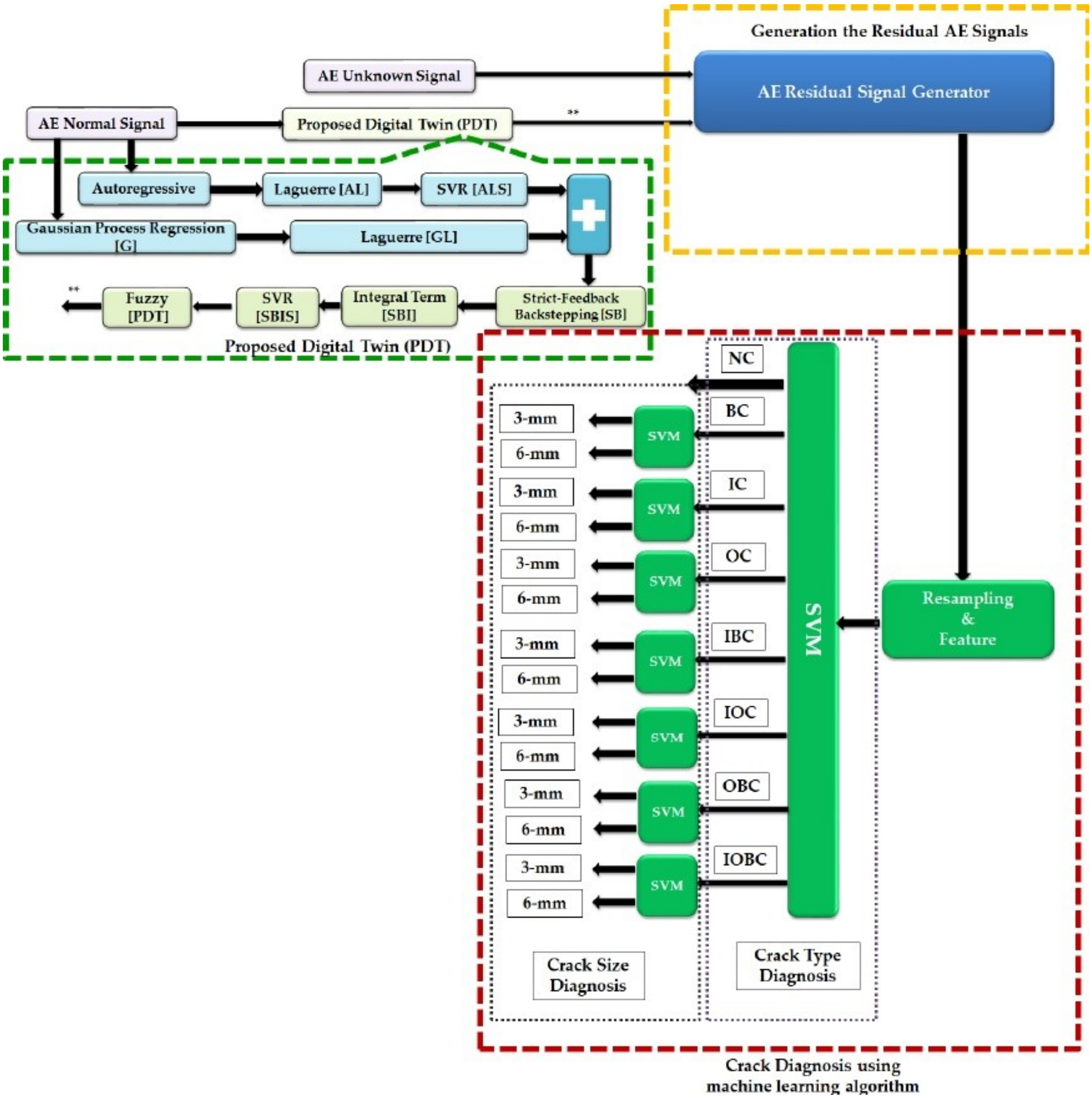

Figure 9. Structure of the proposed digital twin with machine learning for crack type/size diagnosis [61]. **: The output of the proposed digital twin.

4.2. The Mainshaft Bearing Life Analysis Based on Digital Twin

The life analysis of aeroengine mainshaft bearings based on digital twins is one of the most important applications of digital twins. After diagnosing the failure of the mainshaft bearing, it is necessary to predict the remaining service life (RUL) of the mainshaft bearing in time to prevent serious accidents caused by the failure of the mainshaft peripheral bearing during the working period of the aeroengine [66]. The article by Xue Bin [67] pointed out that a method of Remaining Service Life (RUL) Similarity-Based Prediction (SBP) has fewer potential applications in limited instance scenarios, but has been successfully applied to bearing degradation and tool wear prediction. However, the signal transmitted by the sensor will have noise, which affects the prediction accuracy of SBP. Therefore, to establish a predictive model with accuracy and robustness, it is necessary to develop a nonlinear data fusion model that can capture the degradation of complex machinery. Zhang Qiang [68] proposed a new RUL prediction model CRAN, a model based on CNN-LSTM, in order to achieve the high-precision prediction of rolling bearing end-to-end RUL, which effectively combines the powerful feature extraction abilities of CNN and LSTM, has a time-series-processing capability and has higher RUL prediction accuracy than CNN- and

LSTM-based models. Nistane Vinod [69] proposed a fault prediction method that integrates an optimization health indicator (OHIs) and bearing RUL by using a genetic algorithm. This method can be used to predict bearing RUL and, compared with other network prediction methods, it has high prediction accuracy.

Prathamesh S. Desai [70] developed a deep-learning-based digital twin model for predicting the remaining useful life (RUL) of components used in oil and gas plants. RUL data are used to train a multivariate convolutional neural network (CNN) to trigger automatic maintenance without explicitly measuring wear phenomena. Samatar Omar Farah [71] proposed a discrete element method (DEM) based on digital twins and established a DEM-based mechanical model (Figure 10). The model has all the components of the ball bearing, can simulate the motion state of the bearing under load and implements the stiffness model of the elliptical Hertzian contact and the improved elastohydrodynamic (EHD) lubrication formula of the lubricating contact in the numerical tool. A capacitance model related to fluid film thickness and contact pressure is also introduced. The numerical prediction results of the lubricating film capacitance provided by the digital twin are qualitatively and quantitatively consistent with the experimental data. The digital twin model based on the combination of discrete element generation and the capacitance method can provide an optimization scheme of bearing life according to lubricant performance and lubrication state.

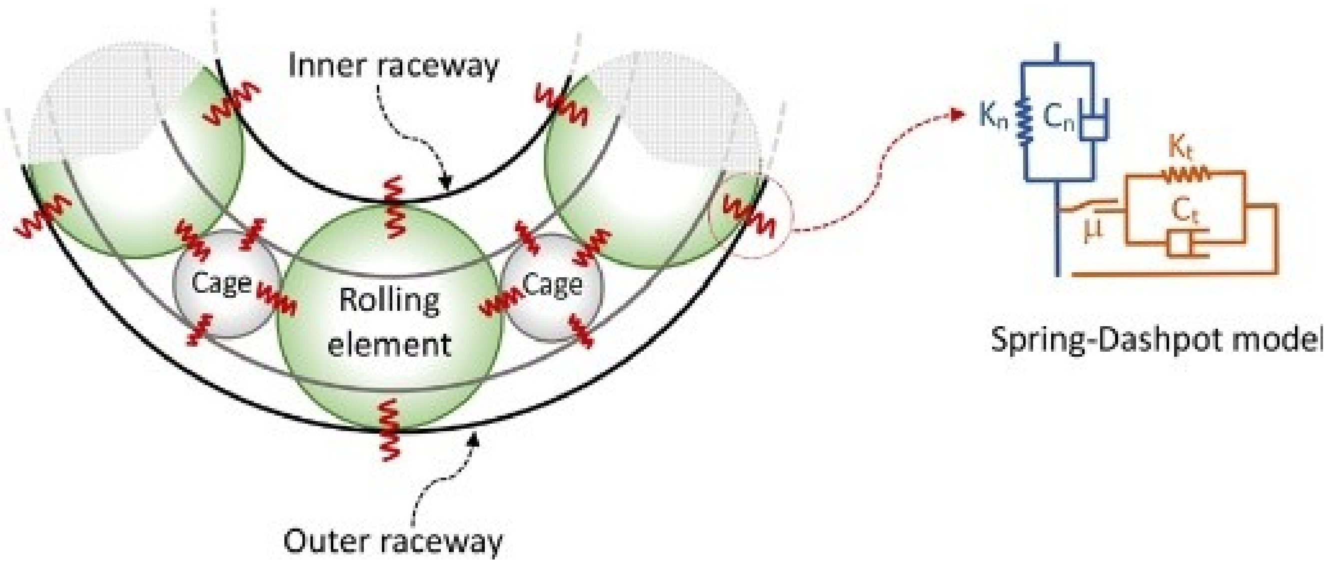

Figure 10. Contact stiffness model [71].

Minglan Xiong [72] established a digital-twin-driven predictive maintenance model of the aeroengine, which predicted the aeroengine RUL with high accuracy. Liu Zhifeng [73] proposed a "super-network-warning feature" fault prediction and maintenance method (Figure 11). Based on the digital twin five-dimensional model [15], this method establishes a three-layer super-network data model consisting of three subnetworks: a data physical layer, a data virtual layer and a data service layer. The model was continuously trained through the process of data acquisition and preprocessing, and finally the method achieved an effective combination of fault prediction and maintenance. Taking an aeroengine bearing as an example, the prediction accuracy after preprocessing of this method is higher than that of the method without preprocessing and the traditional method. Therefore, the fault prediction and maintenance method of the "super-network-warning feature" can effectively predict the life of aeroengine mainshaft bearings.

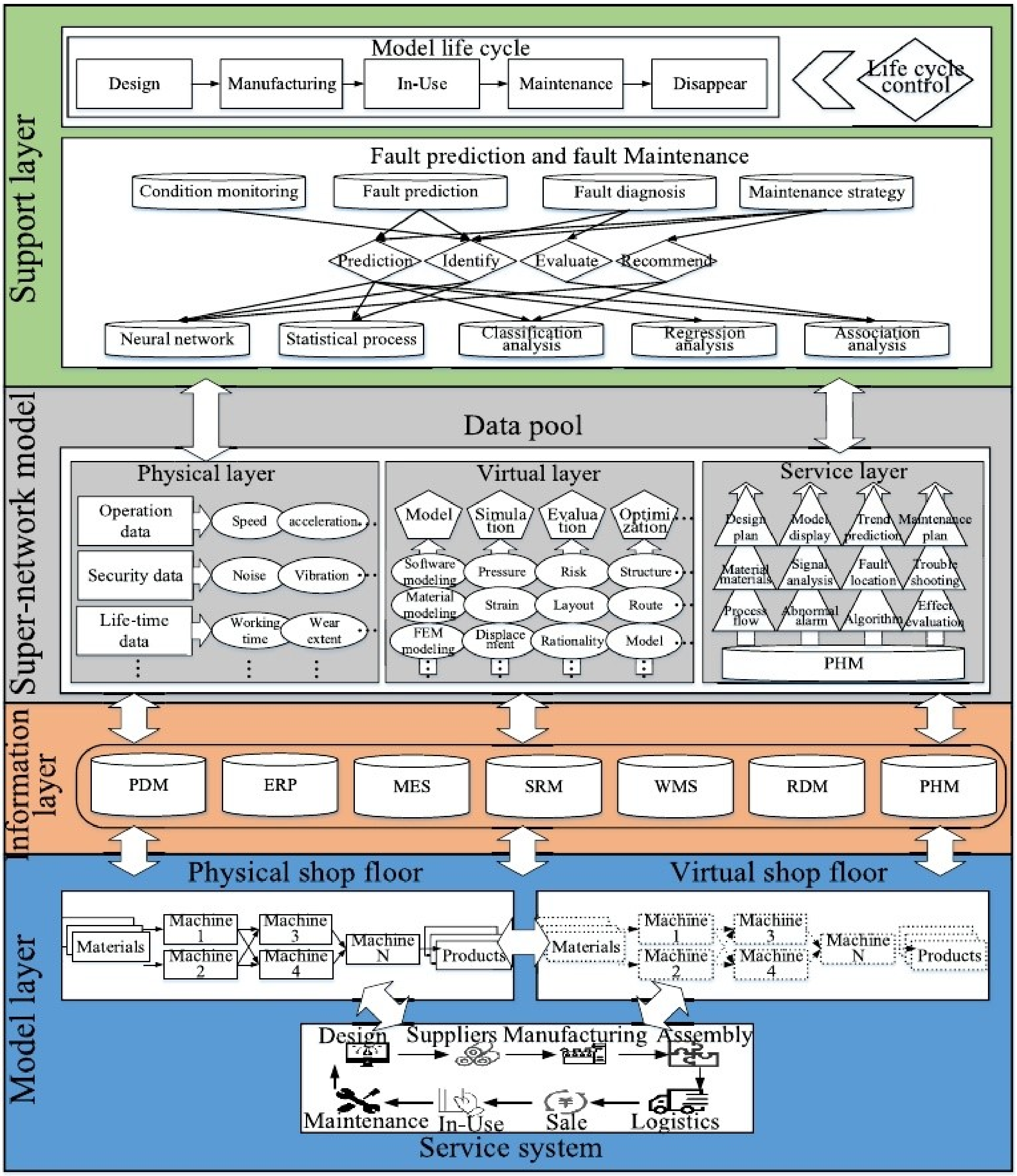

Figure 11. Detailed architecture of the product fault prediction and maintenance strategy [73].

4.3. A Digital Twin Framework for Fault Diagnosis of Aeroengine Mainshaft Bearings

The main purpose of this paper is to propose a digital twin framework for managing the fault diagnosis of aeroengine mainshaft bearings. The framework has the functions of fault diagnosis, simulation optimization and predictive maintenance of mainshaft bearings. The framework integrates the virtual model of the mainshaft bearing, multi-source data and various parameters. The advantage is that each module of the framework has literature to support the advantages and robustness of the digital twins applied to this module. Figure 12 depicts the digital twin framework for aeroengine mainshaft bearing fault diagnosis. The framework consists of seven modules: bearing entity, a data processing module, a bearing model, a fault diagnosis module, a digital twin database, a life analysis module and an optimization maintenance module. Each module is explained in detail as follows:

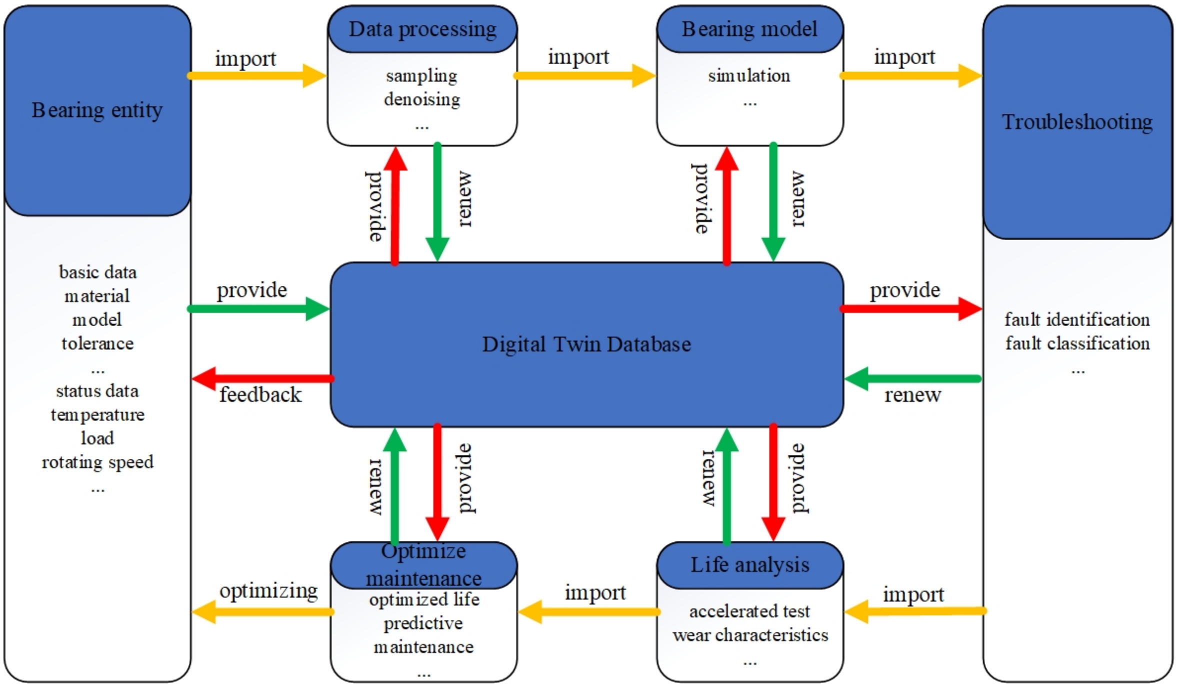

Figure 12. Digital twin framework for aeroengine mainshaft bearing fault diagnosis.

1. Bearing entity: This is the actual entity of the aeroengine mainshaft bearing. It is necessary to input the parameters of the mainshaft bearing in various states into the digital twin framework, and it will be optimized and maintained according to the recommendations given by the digital twin framework. It is the basic data source and the final executed object of the digital twin framework.
2. Data processing module: Due to the large number of mainshaft bearing state parameters monitored by various sensors, such as temperature, speed, vibration, flow, displacement, sound and other parameters, some parameters contain a lot of noise, such as vibration signal and audio signal. The data processing module needs to perform multi-parameter integration and data processing, such as denoising the signal containing noise, extracting fault features and simplifying the signal to be analyzed, to facilitate data transmission and analysis.
3. Bearing model: Mapping of bearing entities. The status data of the bearing entity can simulate the status of the mainshaft bearing in real time, or simulate the status of the mainshaft bearing at any time according to the parameters of the mainshaft bearing in the database, such as the mainshaft bearing dynamics simulation, lubricating fluid dynamics simulation, etc.
4. Troubleshooting Module: The data of the mainshaft bearing are analyzed, numerical algorithms, such as convolutional neural network, support vector machine, etc., are used to intelligently identify the fault type of the mainshaft bearing and classify the fault.
5. Digital Twin Database: The basic dimensional data of the mainshaft bearing are stored, such as material, model, tolerance, etc., as well as all data under working conditions such as temperature, speed, etc. Data are analyzed by all modules in the digital twin framework, such as failure frequency, life, etc. This provides parameter information for the mainshaft bearing simulation model and is the data source for the operation of all other modules.
6. Life Analysis Module: According to the accelerated life experiment of the mainshaft bearing state simulation, the wear characteristics of the mainshaft bearing are analyzed and the influence of each parameter of the mainshaft bearing on the wear life of the mainshaft bearing is evaluate, such as speed, load, clearance, etc., to improve the life prediction accuracy of the mainshaft bearing.

7. Optimize Maintenance Module: According to the results of the life analysis module, a set of maintenance strategies for the existing mainshaft bearings are formulated to optimize the life of the mainshaft bearings. The digital twin framework can also simulate according to the maintenance strategy, find out the deficiencies of the existing strategy and iteratively optimize it to obtain the optimal maintenance strategy and achieve predictive maintenance.

The advantage of the digital twin framework for the fault diagnosis of the aeroengine mainshaft bearings is that the digital twin database includes the digital twin database in the digital twin manufacturing process of the aeroengine mainshaft bearings described in Section 3 above. In the fault diagnosis of the mainshaft bearings, multi-source characteristic data of the mainshaft bearings are integrated, including the basic dimensional parameters, microscopic structural characteristics and manufacturing process information of the mainshaft bearings, so as to improve the accuracy of the fault diagnosis of the mainshaft bearings. The high-precision fault diagnosis results of the mainshaft bearing of the aeroengine are used to analyze the remaining service life of the mainshaft bearing. According to the different working conditions of the mainshaft bearing, the maintenance strategy of the mainshaft bearing is formulated to improve the remaining service life of the mainshaft bearing. All results of the fault diagnosis digital twin framework will be stored in the digital twin database.

The digital twin manufacturing process of the aeroengine mainshaft bearings has the same database as the digital twin framework for the fault diagnosis of the aeroengine mainshaft bearings, and researchers can partially optimize the process of each link in the mainshaft bearing manufacturing process according to the results of the fault diagnosis. For example, the content of inclusions in molten steel can be precisely controlled, the temperature of heat treatment can be increased, the path planning of grinding can be optimized, etc. The manufacturing process of the mainshaft bearings based on digital twins finally improves the manufacturing process level of the aeroengine mainshaft bearings.

The digital twin framework of aeroengine mainshaft bearing fault diagnosis can not only achieve the predictive maintenance of mainshaft bearings but can also achieve the fault diagnosis of mainshaft bearings with higher accuracy. In the case of reducing the experimental cost, high-fidelity and high-precision simulation experiments can also be realized, more experimental data can be obtained and the life of aeroengine mainshaft bearings can be improved.

5. Conclusions

This paper discusses the key issues of integrating the manufacturing and fault diagnosis of aeroengine mainshaft bearings into digital twins and analyzes the research progress of mainshaft bearings based on digital twins from manufacturing to life analysis. The manufacturing process of the mainshaft bearing based on digital twins is discussed, including the metallurgical process, heat treatment process and grinding process of bearing steel, as well as the fault diagnosis and life analysis of the mainshaft bearing based on digital twins. A five-dimensional model-based mainshaft bearing production plan and a digital twin framework for aeroengine mainshaft bearing fault diagnosis is proposed. The digital twin manufacturing process of the aeroengine mainshaft bearings can optimize the structural design of the mainshaft bearings and improve the manufacturing process of the mainshaft bearings based on the results of the digital twin framework for fault diagnosis of the aeroengine mainshaft bearings. From the structural design of the mainshaft bearing of the aeroengine, through the manufacture, analysis and optimization of the mainshaft bearing, to the use stage of the mainshaft bearing, every link can improve work efficiency through digital twin technology. The digital twin framework of the mainshaft bearing manufacturing process and the mainshaft bearing fault diagnosis based on digital twin will finally progress the manufacturing process level in industry and provide breakthrough progress in fault diagnosis.

At present, many breakthroughs have been made in the manufacture and fault diagnosis of mainshaft bearings, but many problems and limitations of digital twin technology for mainshaft bearing manufacturing and fault diagnosis still require continuous research. Among them, the main obstacles hindering the establishment of digital twin models for high-fidelity mainshaft bearing manufacturing and fault diagnosis are the lack of efficient and systematic multi-physical surface generative modeling methods and online measurement methods to identify and distinguish different parameters, as well as the lack of proper data analysis and requirements for computational efficiency. In the future, the development of digital twins will continue to fulfill the requirements of all aspects.

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