Research on Health Monitoring and Intelligent Diagnosis Technology of Large-Scale Low-Speed Wind Tunnel

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Abstract. The large-scale low-speed wind tunnel test system is complex, involving many equipment, parameters, and data. In order to monitor the state of the system, quickly determine and locate the cause of the fault when the system is abnormal. Based on advanced sensors and network technology, this paper monitors the components and parameters of the system in real time. Through the three-dimensional simulation method, the digital twin system construction of the wind tunnel system including the model is realized, and the data visualization method is combined with the machine learning technology to intelligently predict and diagnose the faults and causes of the test data. Through the research in this paper, the technical foundation is laid for the construction of the smart wind tunnel laboratory.

Keywords: Low-speed wind tunnel health monitoring · Fault diagnosis · Digital twin · Deep learning · Artificial intelligence

1 Introduction

The concept of health monitoring and intelligent diagnosis was first proposed by the United States in 1998 during the research and development of its F35 joint attack aircraft, with the purpose of improving the safety and survivability of fighters [1]. Since then, the failure prediction and health management system has played a big role in the military field [2], and it has attracted the attention of military powers in the world. Nowadays, Prognostic and Health Management (PHM) technology has been continuously developed from the original military field to private enterprises [3], and is widely used in the maintenance of new-generation equipment in the fields of transportation, equipment manufacturing, power generation, etc. [4]. Such as aircraft, ships, vehicles, CNC machine tools, etc. Boeing applied PHM technology to civil aviation and developed an aircraft health monitoring system [5]. The system collects flight status data in real time, and makes maintenance decisions after failure analysis [6], Maintenance personnel can log on the website to obtain fault information, and realize the integration of network system functions [7]. NASA is also studying PHM technology as an important

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part of aviation maintenance [8]. Bai et al. proposed a multi-objective CBM optimization method, using PHM technology to systematically balance the relationship between optimization objectives and find the optimal solution that best represents the decision maker's preference [9]. Moussa Hamadache, Joon Ha Jung, etc. based on REB prediction and PHM technology, introduced different bearing failure modes, outlined modern PHM technology, and explored deep learning methods for bearing fault detection and diagnosis [10].

The concept of failure prediction and health management has also attracted extensive attention of domestic scholars [11]. In 2015, based on the monitoring system and data acquisition, Huang Lili proposed the PHM technology of wind turbine operation and maintenance data, which is used for the condition assessment and fault diagnosis of wind turbines, and designed and developed the prototype control system of wind turbine PHM [10]. Wang Tianyu, Wang Hongdong and others used Bayesian network to establish a reliability model, and studied the application of this model in PHM, predicting the failure time of unmanned ships, and monitoring their health in real time [12]. Guo Yangming, Mi Qi et al. combed the technical connotation of PHM and the system architecture of avionics, and gave a dynamic reconstruction model of distributed integrated modular avionics based on PHM, which provided the foundation and guarantee for avionics [13]. Cui Liming applied PHM technology to bearings, and used AR model to extract the characteristics of bearing degradation trend and predict its service life [14].

The large-scale low-speed wind tunnel test system has a complex composition, involving many sections and their associated sensors; there are many types of wind tunnel tests, the test parameters are diverse, the data processing process is complex, and the test accuracy is extremely high. The use of health monitoring and intelligent diagnosis technology to carry out intelligent operation and maintenance management of wind tunnel has important research significance and application value for improving the stability of wind tunnel operation, wind tunnel test efficiency and test accuracy.

The FL-10 wind tunnel of the AVIC Aerodynaiviics Research Institute is currently the largest production-type low-speed wind tunnel in China. The size of the test section is 8 m $\times$ 6 m. In this paper, based on this wind tunnel, research work on health monitoring and intelligent diagnosis technology is carried out, and a large-scale low-speed wind tunnel health monitoring system is built. Its interior covers high-fidelity models such as factory areas, movable wind tunnel sections, test equipment, test models, and components based on 3D vision; digital mapping of test equipment and test status driven by multi-source data fusion such as real-time data and CFD simulation data; use multi-dimensional sensor network to realize the health monitoring of test equipment and parameters, realize equipment predictive maintenance, fault detection and diagnosis through artificial intelligence technology. Finally, a digital and intelligent wind tunnel management platform with multi-dimensional sensors as the skeleton, artificial intelligence and machine learning technology as the main body, and digital twin as the terminal embodiment will be realized.

2 Design of Health Monitoring System for Large-Scale Low-Speed Wind Tunnel

2.1 Identification of Wind Tunnel Monitoring Factors

Based on the expert knowledge base and the historical operation experience of the wind tunnel, the factors of each subsystem and equipment of the FL-10 wind tunnel are identified, and the key systems and equipment that affect the test efficiency or test data quality are determined. It mainly includes power system, cooling system, support system, wind tunnel body, etc. Health monitoring, fault diagnosis and predictive maintenance of the above subsystems and their ancillary equipmen, It will improve the reliability of equipment and facilities, ensure the long-term stable operation of the wind tunnel test environment to the greatest extent, and provide favorable quality assurance for obtaining effective and accurate test data.

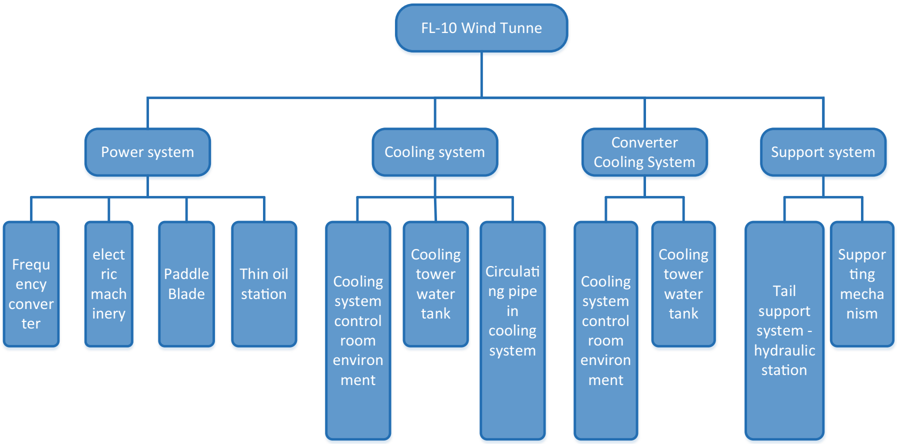


Fig. 1. Identification of monitoring factors in FL-10 wind tunnel

2.2 Sensor Arrangement and Networking

Divide the FL-10 wind tunnel according to the system identified in Fig. 1. Arrange sensors in the key sections of the wind tunnel and the necessary points of the auxiliary equipment of each subsystem and form a network. The sensor monitoring network covers all key systems and equipment of the entire FL-10 wind tunnel. Segments and equipment, so as to achieve a full range of health monitoring and fault diagnosis for the FL-10 wind tunnel system.

The signals of the power system monitoring objects are mainly inverter fault information, temperature information of the motor rotor and bearing bush, and shaft vibration information. The signals of the monitoring objects of the cooling system are mainly cooling tower water level and temperature information, cooling water pipeline pressure, flow and inlet and outlet temperature information. The signals of the monitoring object of the support system are mainly the vibration information of the support system, the pressure information of the hydraulic tail support pipeline, the liquid level of the fuel tank in the pump station, and the temperature information. The specific sensor arrangement is shown in the Table 1.

The data required for wind tunnel health monitoring and intelligent diagnosis algorithms are collected from the underlying data acquisition layer by PLC and field sensors, and then entered into the central switch of the test network through the data access layer switches of each subsystem and data acquisition system. The aggregated data is sent to the wind tunnel equipment operation database for storage to form a historical database, which is used as the basic training data for algorithm modeling. At the same time, the real-time data is transmitted to the health monitoring system server, and the health monitoring and intelligent diagnosis algorithms are used for real-time calculation and analysis. The data networking result is shown in the following Fig. 2.

2.3 Monitoring System Based on Sensor Network

Figure 3 is a monitoring system of a sensor network arranged in the health monitoring and intelligent diagnosis system of the system. The operation interface of the monitoring system takes the top view of the FL-10 wind tunnel as the main body and is divided into subsystems, and its content covers all the sensor parameters in Table 1. The key information such as the system, equipment running status, and test progress status can be visually viewed in the wind tunnel. When the sensor parameters are abnormal, the interface will flash and turn red to give an alarm.

3 Construction of Digital Twin System

3.1 3D Scene Digital Reconstruction

High-fidelity 3D scene reconstruction of large-scale low-speed wind tunnel health monitoring and intelligent diagnosis system is to use 3Dmax software to carry out high-fidelity and refined modeling and reconstruction of FL-10 wind tunnel scene and internal test section equipment. Built-in three-dimensional digital model including the overall structure of the test section, the floor and tail support linkage mechanism, the floor and turntable linkage mechanism, the open test scene, and the closed test scene; switchable test model groups including civil aircraft standard models, military aircraft standard models, missile models, and train models can be quickly imported through 3D scanning technology, It also includes the test support system model group including hydraulic tail support, single rod support, turntable support, etc. The system can freely switch the test type, support mechanism, and support form according to the actual test scene of the wind tunnel, and finally realize the 3D high-fidelity digital scene reconstruction based on the FL-10 wind tunnel (Fig. 4).

Table 1. Equipment status monitoring table

Monitoring system	Monitoring content	Monitoring variables	Number of sensors
Power system	Inverter	Inverter temperature	1
		Inverter voltage	1
		Inverter power	1
		Inverter current	1
		Inverter power-on indication	1
		Inverter fault indication	1
		Inverter running indication	1
	electric machinery	Motor stator temperature	5
		Motor noise	4
		Motor vibration	4
		Motor bearing bush temperature (thrust, radial)	4
		Axial movement of motor	1
	Paddle Blade	Blade stress	9
	Thin oil station	Low pressure state of thin oil station	1
		Operation indication of high pressure pump in thin oil station	2
		Operation indication of low pressure pump in thin oil station	2
Wind tunnel cooling system	Cooling tower water tank	Tank temperature	11
		Tank level	11
		Ambient temperature and humidity	2
	Circulating pipe in cooling system	Discharge	1
		Water temperature	1

(*continued*)

Table 1. (*continued*)

Monitoring system	Monitoring content	Monitoring variables	Number of sensors
		Hydraulic pressure	1
	Cooling system control room environment	Ambient temperature and humidity	2
Converter cooling system	Converter cooling system	Internal circulation cooling water pump shell temperature	2
		Internal circulation cooling water level	1
		Internal circulation cooling water flow	1
		Inlet temperature of internal circulation cooling water	1
	External circulation cooling system	External circulation cooling pressure	1
		External circulating cooling water temperature	1
Support system	Tail support system—hydraulic station	Oil tank temperature	1
		Tank level	1
		Fuel tank supply pressure	2
	Supporting mechanism	Voltage	1
		Electric current	1
		In cylinder displacement becomes (actual angle of attack,α)	1
		In cylinder displacement (sideslip angle, $\beta 1$)	1
		Fault indication	1
		Operation indication	1
		Tail brace height	1

3.2 3D Digital Test Scene Mapping

The 3D model established by the fusion of real-time equipment operation data, CFD simulation data, test data and other multi-source data is driven to realize the digital

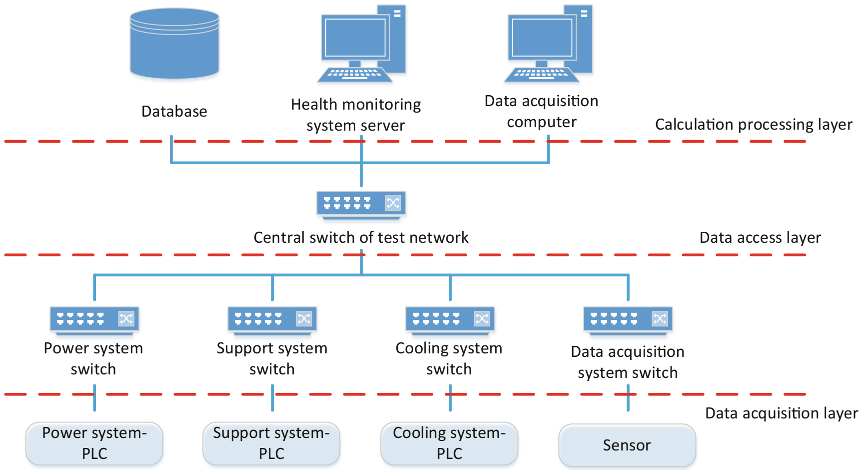
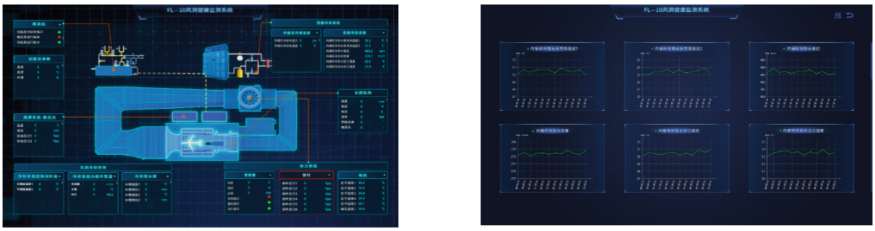


Fig. 2. Sensor network architecture diagram



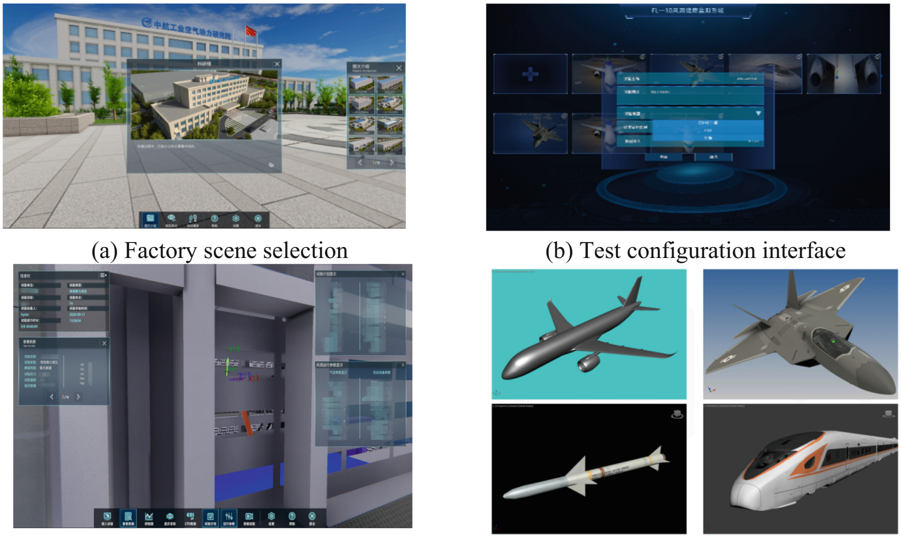
(a) FL-10 wind tunnel monitoring system (b) Sensor data monitoring

Fig. 3. Monitoring system based on sensor network

mapping of test equipment and test status. For the model attitude angle data, the system performs Inverse Kinematics (inverse dynamics) calculation after obtaining the target value, and controls the synchronous change of the movable joints of the support mechanism to achieve the effect that the dynamic attitude angle of the test target is consistent with the actual test linkage angle. For the change of the test target's own components, the system correspondingly obtains the names and positions of the detachable components, and performs simultaneous display and concealment operations according to the test plan, so as to realize the structure and the key components of the test target (such as wings, landing gear, vertical tail, horizontal tail, etc.) High consistency of actual trials (Fig. 5).

3.3 Flow Field Visualization Technology Based on CFD Simulation Data

The health monitoring and intelligent diagnosis system built in this study has a built-in flow field visualization module based on CFD simulation data. Its specific implementation is as follow.



(a) Factory scene selection

(b) Test configuration interface

(c) Digital reproduction of equipment scene and parameters

(d) Built-in model library of the system

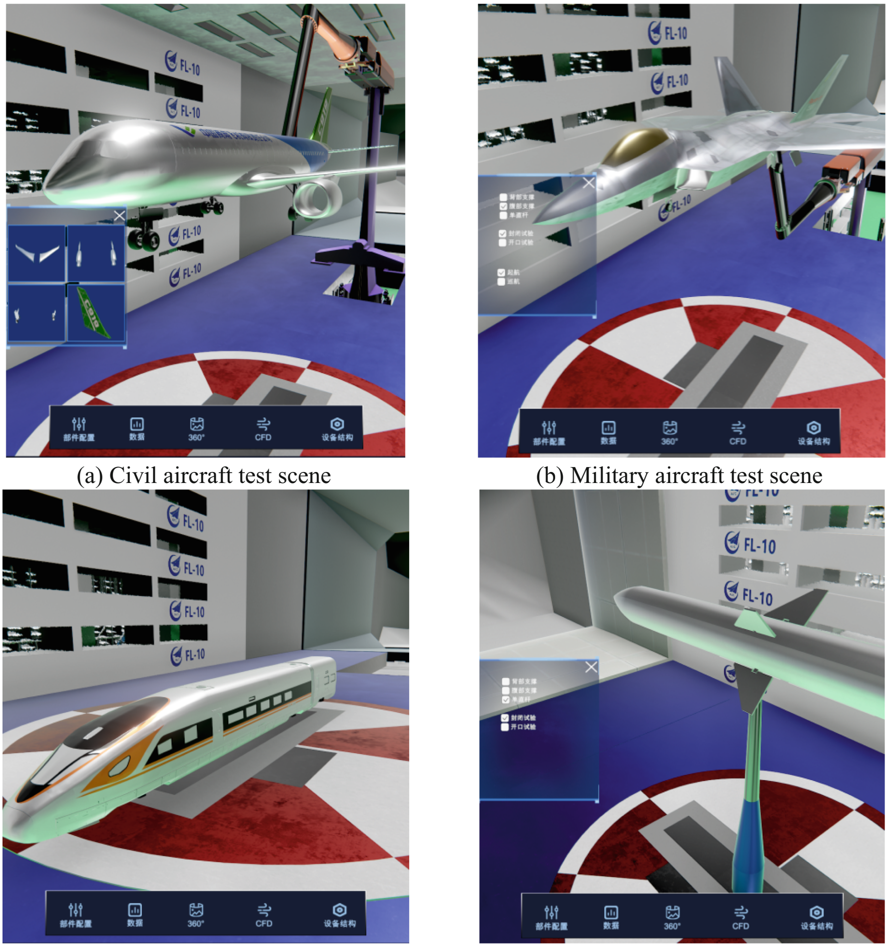
Fig. 4. Digital construction of high-fidelity 3D scene

The point cloud data calculated by CFD is extracted and processed, and each point data is positioned in three-dimensional space coordinates, and given specific meanings such as three-dimensional space coordinates, time series, and pressure coefficients. It adopts the development idea of Unity physics engine + distributed loading method, and has a data point reduction algorithm, which automatically filters some points according to the set rules and optimizes the point information, effectively solve the problem of slow loading and freezing of 3D visualization due to large amount of data, it can perform distributed fusion loading processing on millions of point cloud data, and display the effect in real time. The point cloud data is given different chromatographic colors according to the size of the CFD calculation data, and the calculation is comprehensively summarized, so as to realize the three-dimensional flow field visualization based on the CFD simulation data (Fig. 6).

4 Research on Data Intelligent Diagnosis Technology Based on Equipment Parameters

4.1 Key Equipment Prediction Learning Machine Based on Machine Learning

At present, conventional equipment health monitoring algorithms use a machine learning or deep learning algorithm to predict key equipment characterization parameters. Although this method can achieve a certain level of accuracy, due to the different spatial complexity of different algorithms and the possible selection of Not the best algorithm for the current data. As a result, although the accuracy meets the requirements, the



(a) Civil aircraft test scene

(b) Military aircraft test scene

(c) High-speed rail test scene

(d) Missile test scene

Fig. 5. Three dimensional digital mapping of test scene

selected algorithm is not the optimal algorithm, and it takes a lot of time to select the algorithm. In response to this situation, this paper proposes a key equipment health monitoring learning machine, which combines several algorithms suitable for wind tunnel health monitoring, and the learning machine compares the accuracy of each algorithm and various statistical indicators. Pick the optimal algorithm that fits the current running data. In this way, a more accurate prediction algorithm can be found clearly and quickly.

According to the historical operation data of the equipment, four machine learning algorithms including SVR (Support Vector Machine Regression), ElasticNet (Elastic Network Regression), Gauss (Gaussian Mixture), and GRU (Gated Neural Network) are combined to form a large-scale low-speed wind tunnel key equipment health monitoring learning machine. During algorithm training, the predictive learning machine forms four different algorithm models, and the learning machine independently judges statistical

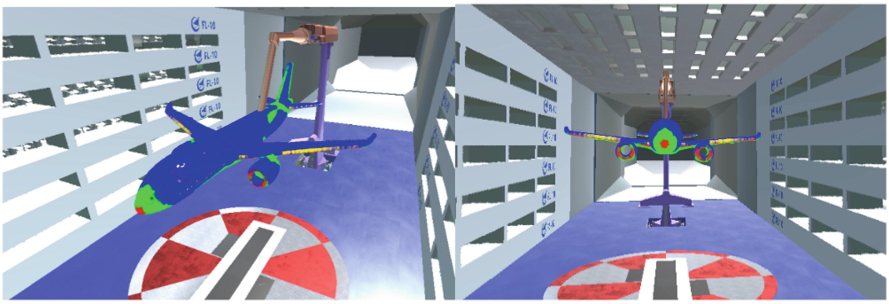


Fig. 6. Flow field visualization technology based on CFD simulation data

indicators such as fit, root mean square error, etc., and selects the algorithm with the highest fit and the smallest error as the final prediction algorithm.

4.2 Health Monitoring and Intelligent Diagnosis Algorithm

Data Processing

In this paper, six months of historical operating data of the wind tunnel were selected as the modeling data for the predictive learning machine. Based on the identification of key equipment in the wind tunnel based on expert experience, the motor speed is finally determined as the output parameter of the health monitoring algorithm; with 39 types of characteristic variables deployed by subsystems such as motors, frequency converters, propellers, and thin oil stations, a total of 86 characteristic values are the key factors affecting the motor speed. The algorithm structure is shown in the following Fig. 7.

Standardization

Since the variable data vector dimension and unit required to be monitored by the wind tunnel monitoring system are quite different [15], in order to improve the convergence speed of the predictive learning machine, the input data is standardized and preprocessed [16]. The formula is as follows:

$$S_n^k = \frac{X_n^k - \frac{1}{K}\sum_{K=1}^{N} X_K^n}{\sqrt{\frac{1}{K-1}\sum_{K=1}^{N}(X_K^n - \frac{1}{K}\sum_{K=1}^{N} X_K^n)^2}} \tag{1}$$

In the formula: X_n^k represents the production parameters of the Kth sample under n-dimensional data standardization, S_n^k represents the n-dimensional metadata of the Kth sample arranged in a time series, and K is the number of data sets.

Health Monitoring Algorithm of Key Equipment

The health monitoring prediction learning machine proposed in Sect. 3.1 is used to predict the historical operation data of the wind tunnel. The learning machine predicts the output curve as follows.

Table 2 lists the fit, MAE, MSE and RMES errors of the four regression algorithms SVR, ElasticNet, Gauss, and GRU to the wind tunnel historical data.

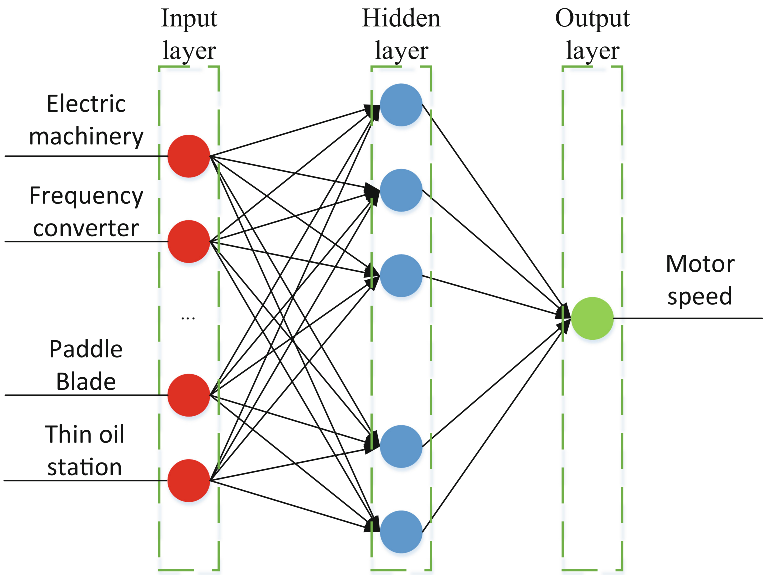


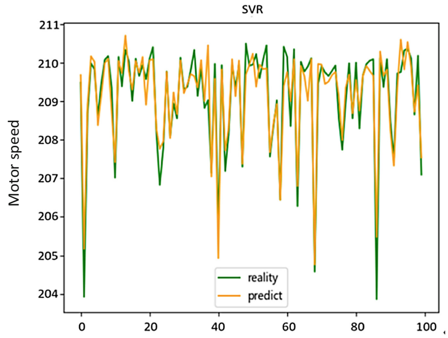
Fig. 7. Health monitoring algorithm structure

The following conclusions can be drawn from Fig. 8 and Table 2: the predicted value of the GRU algorithm has the best fit, and the errors of MAE, MSE and RMES are the smallest. Therefore, the model established by the GRU algorithm is selected as the prediction algorithm for the health monitoring of this system.

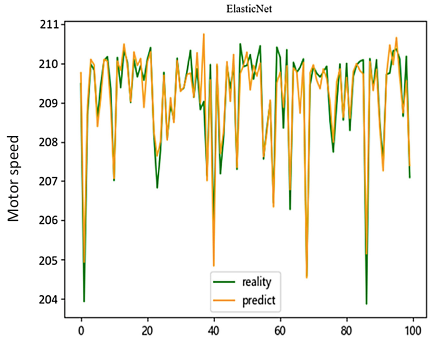
Failure prediction algorithm of key equipment

This study is based on a large amount of historical data with time series properties running in the wind tunnel, and uses the Bi-LSTM (Bi-directional Long Short-Term Memory network) algorithm to model it. The Bi-directional Long Short-Term Memory network is based on LSTM and combines the input The information of the sequence in both forward and backward directions, for the output at time t, the forward LSTM layer has the information at time t and before in the input sequence, and the backward LSTM layer has the information at time t and later in the input sequence. Information. The output of the forward LSTM layer at time t and the output of the backward LSTM layer at time t are processed together as the final algorithm prediction output. The structure of the Bi-directional Long Short-Term Memory network algorithm is shown Fig. 9.

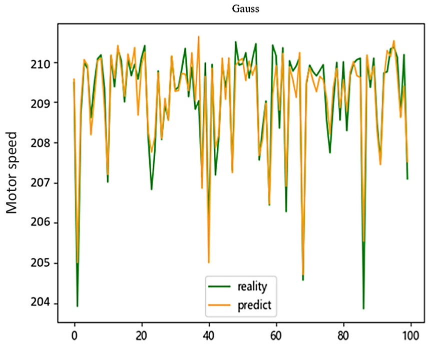
In the Bi-directional Long Short-Term Memory network, the neural network model not only uses the data information before the current moment in the historical data, but also fully considers the data information that occurs in the future [17]. The purpose of the fault prediction algorithm established for the key equipment of the wind tunnel is to predict the operation status of the equipment for a period of time in the future. Therefore, when training the algorithm model, it is more suitable to choose the Bi-directional Long Short-Term Memory network, and fully learn the historical operation



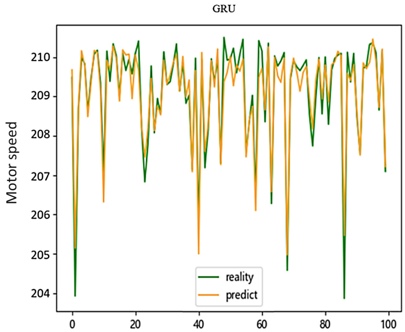
(a)SVR prediction curve



(b)ElasticNet prediction curve



(c)Gauss prediction curve



(d)GRU prediction curve

Fig. 8. Predictive learning machine prediction output curve

Table 2. Predictive learning machine output evaluation indicators

	R^2	MAE	MSE	RMSE
SVR	0.9009	1.5922	4.9379	2.2221
ElasticNet	0.9054	1.5497	4.7181	2.1721
Gauss	0.8991	1.6110	5.0318	2.2432
GRU	0.9314	1.2050	3.5232	1.8770

process of the equipment from the forward and reverse directions, which can greatly improve the model's ability to cope with sudden changes and abnormal moments.

For the input data of the Bi-LSTM network, the construction of feature engineering needs to be added on the basis of the data processing process described in Sect. 3.2.1. In this paper, the sliding window algorithm is used to construct feature engineering for historical data.

The sliding window algorithm is to predict the future data of the device, expand the value range of the current moment to an interval including this point, and use the

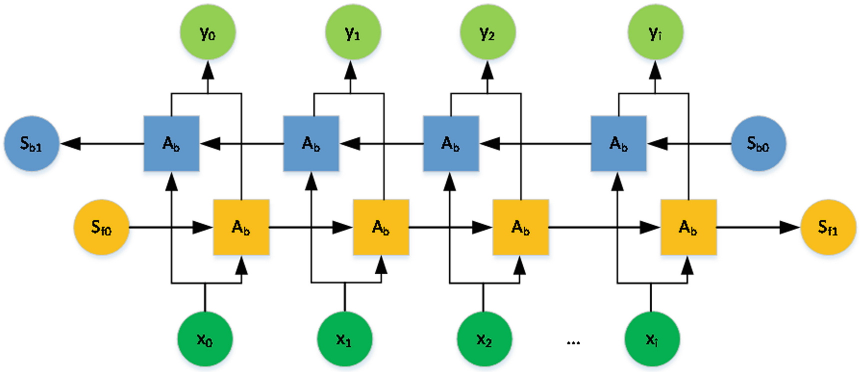


Fig. 9. Bi-LSTM algorithm structure diagram

interval to judge, this interval is the sliding window. The sliding window is to select the corresponding time series according to the specified unit length, so as to calculate the statistical indicators in the window. Its principle is shown in the Fig. 10.

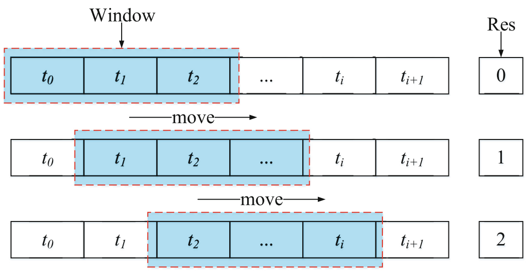


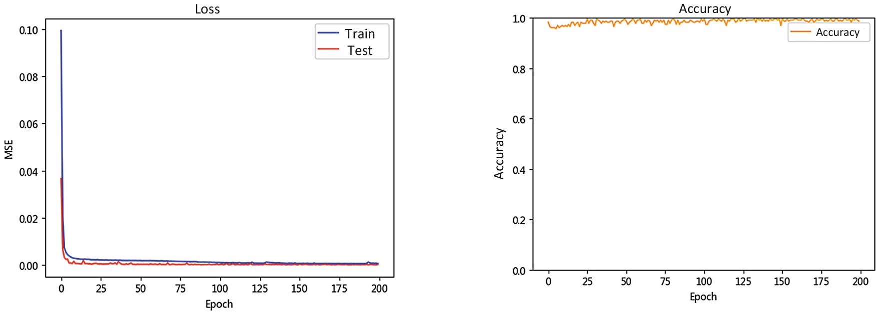
Fig. 10. Example of sliding window.

The following figure shows the error curve and accuracy of the mathematical model built by the Bi-LSTM network based on the above historical data. It can be seen from the figure that the algorithm reaches the optimum at the 125th iteration, the mean square error reaches e-4 level, the accuracy rate is close to 1, and the training error and test error are converged well, no overfitting or underfitting in the established model (Fig. 11).

In this paper, the sliding window size is selected as 30, that is, the data points of the past 30 moments are considered to predict the equipment operation trend of the next 3 moments. The figure below shows the prediction curve of the fault prediction algorithm based on the Bi-LSTM network. The blue curve in the figure is the prediction curve of the fault prediction algorithm for the running state of the motor speed at the next three moments (Fig. 12).

Intelligent fault diagnosis algorithm of key equipment

Due to the wide variety of equipment in the wind tunnel, the failure modes and failure mechanisms are very different, and the procurement time of each equipment is not



(a) Bi-LSTM algorithm error curve (b) Bi-LSTM algorithm accuracy

Fig. 11. Bi-LSTM algorithm error and accuracy curve

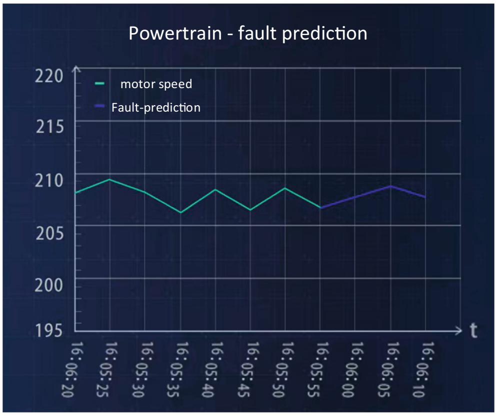


Fig. 12. Prediction output of fault prediction algorithm

uniform, resulting in different equipment operation data storage conditions, and it is difficult to use a fixed diagnosis method to meet the fault diagnosis requirements. Taking into account comprehensively, this system uses the combination of expert experience and principal component analysis (PCA) to diagnose the faults of the key equipment of the FL-10 wind tunnel.

PCA is to project high-dimensional process data into an orthogonal low-dimensional subspace and preserve the main process information [18]. Geometrically, the coordinate system formed by the sample is rotated to a new coordinate space through a certain linear combination, and the new coordinate axis represents the direction with the largest variance [19]. The statistical indicators of the intelligent diagnosis of the PCA algorithm are as follows:

The SPE indicator measures the change of the projection of the sample vector in the residual space [20].

$$SPE = \|(I - P \cdot P^T) \cdot x\|^2 \leq \delta_\alpha^2 \quad (2)$$

where δ_α^2 represents the control limit with confidence α. Its formula is as follows:

$$\delta_\alpha^2 = \theta_1 \left(\frac{C_\alpha \sqrt{2\theta_2 h_0^2}}{\theta_1} + 1 + \frac{\theta_2 h_0 (h_0 - 1)}{{\theta_1}^2} \right)^{1/h_0} \tag{3}$$

Finally, fault diagnosis is performed by calculating the contribution rate.

The SPE-based contribution graph is defined as:

$$Cont_i^{SPE} = (\xi_i^T (I - PP^T)x)^2, i = 1, \ldots, m \tag{4}$$

After the data is calculated and analyzed by the intelligent diagnosis algorithm, the three largest variables in the contribution graph are taken as the most likely cause of the fault, and combined with the expert knowledge base to make a comprehensive judgment. Finally, the precise cause of equipment failure and corresponding operation suggestions are given.

4.3 Implementation and Verification of Health Monitoring and Intelligent Diagnosis Technology

Implementation of Health Monitoring and Intelligent Diagnosis Technology

The working principle of the health monitoring and intelligent diagnosis system is as follows.

Through the established key equipment prediction learning machine, real-time prediction and analysis of the operating state of the key equipment in the wind tunnel are carried out. When the real-time acquisition value of the equipment operation and the predicted value of the learning machine have deviations beyond the allowable error range, the system sends a fault early warning signal; When the fault prediction curve exceeds the preset threshold, the system sends a fault early warning signal. The front-end interactive platform triggers the alarm information, the monitoring interface flashes and turns red and the alarm window pops up.

When the system receives an early warning signal from the health monitoring or fault prediction module, the system automatically enters the intelligent diagnosis module to perform fault diagnosis on the data at the current fault time. At the same time, a fault operation suggestion library is formulated based on expert experience, and finally gives the equipment fault cause and information. Corresponding action suggestions.

Verification of Health Monitoring and Intelligent Diagnosis System

In this paper, the failure of the large motor of the wind tunnel power system “Axial displacement of motor”, which has a great impact on the operation of the wind tunnel, is selected to verify the system.

As shown in Table 1, for the axial movement of the motor, the system arranges a laser displacement sensor at the front end of the motor shaft section. The sensor is zeroed at the midpoint of its range, and the range is ±5mm. The normal fluctuation range threshold is set to ±3mm. In this paper, 100 groups of sensor monitoring network real acquisition values are selected when the wind tunnel system is running normally, and the "motor shaft" in each group of data is manually modified within the interval of [+3.5, +5] ∪ [−5, −3.5] The collected value of the "Axial displacement of motor". This data is input into the health monitoring and intelligent diagnosis system as a verification of the reliability of the system.

The figure shows the contribution of the 86 feature variables output by the intelligent diagnosis algorithm to the current fault data when one set of data is input. The intelligent diagnosis algorithm automatically selects the three characteristic variables with the largest contribution rate, and their histograms are displayed in red. The contribution rates of the remaining features are shown as blue histograms. In the figure, the feature variable with the highest contribution rate is the tag number 25, and the corresponding sensor in Table 1 is "Axial displacement of motor". The contribution rate of this feature is 73.7%, that is, 73.7% may be the fault cause of "excessive axial movement of the motor", and the contribution rates of other sensors are far lower than this cause, so they are not considered. It is confirmed that the intelligent diagnosis algorithm is accurate for the current fault judgment (Fig. 13).

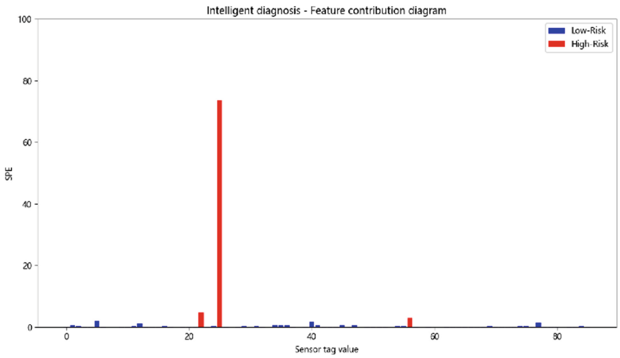


Fig. 13. Contribution rate of each sensor

The overall verification results are shown in the following table.

Table 3. Health monitoring and intelligent diagnosis system verification

Data quantity	Error data value range	Health monitoring alarm times	Accurate times of intelligent diagnosis
30	[+4.5, +5] ∪ [−5, −4.5]	28	27
30	[+4.0, +4.5] ∪ [−4.5, −4]	28	25
40	[+3.5, +4] ∪ [−3.5, −4]	36	33

It can be seen from Table 3 that among the 100 sets of artificially manufactured fault data for "excessive motor axial movement", 60 sets of data are in the interval [+4, +5]

∪ [−5, −4], the alarm rate of health monitoring can reach 93.3%, and the accuracy rate of intelligent diagnosis has also reached 86.7%. In [+3.5, +4] ∪ [−3.5, −4], which is 40 groups of data close to the correct data value range, the accuracy of health monitoring is 90%, and the accuracy of intelligent diagnosis is 82.5%. The combined accuracies are 92% and 85%, respectively. It has been confirmed that the system has good engineering practical value. The actual operation effect is shown in the Fig. 14.

(a) Health monitoring and warning interface

(b) Fault diagnosis and operation suggestion interface

Fig. 14. Front-end interactive interface of fault diagnosis module

5 Conclusion

Identify the key sections and equipment of the FL-10 wind tunnel based on expert experience. Based on advanced sensors and networking technology, through the interactive interface with the overall view of the wind tunnel as the background, each subsystem and ancillary equipment of the wind tunnel are identified. Carry out real-time monitoring to realize the monitoring of the operating status covering the entire area of the wind tunnel.

Based on the high-fidelity 3D model driven by multi-source data fusion such as equipment real-time operation data, simulation data, test data, etc., the virtual-real combination of test equipment, test status and CFD point cloud is realized. Highly digital mapping of the internal test scene, test process and equipment operation status of the wind tunnel, so as to reduce the labor cost of wind tunnel management.

Based on the predictive learning machine based on machine learning proposed in this paper, an optimal algorithm for health monitoring of key equipment in wind tunnels can be quickly found, and the real-time operating status of the equipment can be accurately predicted; fault prediction based on Bi-LSTM algorithm The algorithm can predict the future time of the equipment, and realize the health management and predictive maintenance of the key equipment; Based on expert experience and principal component analysis, the intelligent fault diagnosis algorithm is developed to realize intelligent diagnosis of key equipment, reduce maintenance pressure, and improve the reliability of wind tunnel operation.

The large-scale low-speed wind tunnel health monitoring and intelligent diagnosis system drives the business management process with multi-source data fusion of wind tunnel operation, which improves the informatization and intelligence level of wind tunnel equipment operation management; at the same time, it is involved in advanced technologies such as the Internet of Things and machine learning. Technology, so that it has played an active role in the management and maintenance of key sections and equipment in the wind tunnel; improve the intelligent and automated fault diagnosis of key equipment in the wind tunnel, timely detect latent faults and predict development trends, play a role in The advantages of modern big data and artificial intelligence technology development; finally, it is visually presented in the form of a high-fidelity wind tunnel digital twin to improve the intuitiveness and convenience of wind tunnel management. This system greatly improves the work efficiency of the wind tunnel and the reliability of equipment operation, thereby ensuring the high-quality and high-precision operation of the wind tunnel test.

For the prospect of the research content of this paper, the wind tunnel digital twin operation and maintenance system built in this paper is currently only based on the key equipment and parameters of the wind tunnel to carry out the application of health monitoring and intelligent diagnosis technology. In the future, the small sample data characteristics of wind tunnel tests will be considered, and auxiliary analysis technologies such as intelligent prediction and intelligent diagnosis of wind tunnel test data based on small sample data will be added to the system to expand the application scope and engineering practicability of the system.

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