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Research progress of aero-engine gas-path fault diagnosis technology based on machine learning

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ABSTRACT

With the rapid development of machine learning in various fields, the machine learning method has been gradually applied to aero-engine gas-path fault diagnosis technology. These are gas-path fault problems that have characteristic of large volume of data, high dimension and strong randomness, that is exactly the key innovation point of using machine learning to predict gas-path fault problems. It has been preliminarily developed in the field of gas-path fault diagnosis now, which application value will be confirmed. Machine learning and gas-path fault diagnosis methods are taken as the research background in this thesis. Firstly, the research progress of gas-path fault diagnosis methods for aero-engines is expounded. Secondly, this is introduced the application principle and function that the fusion method of computational fluid dynamics (CFD) simulation gas-path parameters and machine learning algorithm in gas-path fault diagnosis technology. Finally, the challenges and prospects of gas-path fault diagnosis methods the machine learning are discussed profoundly.

Keywords: Machine learning; gas-path fault; gas-path parameters

INTRODUCTION

Engine is the core of aero-aircraft power system. Flight safety will be seriously affected, once the performance failure or sudden failure occurs. According to incomplete statistics, it was found that more than 90% of the problems of aero-engine faults that were derived from the faults of engine gas-path components, and the maintenance cost accounts for more than 60% of the overall maintenance cost of the engine[1]. Therefore, it is very necessary to develop a diagnostic technology to obtain the location of the engine disease accurately and quickly. It is a great significance to improve flight safety, reduce maintenance frequency and cost.

However, Prognostics and Health Management (PHM) technology can realize the prediction of system failure or fault a period of time that complex gas-path systems at the end of the last century, and it provides accurately judgment for the location and type of fault when a fault occurs[2]. The gas-path faults are identified, located and predicted by the variation of gas-path characteristic parameters, thus, it provides a basis for the support maintenance center[3].

After investigation, it was found that the current aero-engine gas-path fault diagnosis technology still faces the following difficulties[4]:

1) It is the vast majority of engine models still to be confronted with problems that the number of measured gas-path parameters less than the number of unknown characteristic parameters, which were obtained the engine gas-path datum by the sensors.

2) The deviation between the gas-path parameters and the noise measured by the sensor due to the gas-path fault is of the same magnitude, so it is still a challenge to extract the characteristic parameters. Thus, the measured characteristic signals are biased to some extent.

3) Gas-path fault testing is not only costs expensive, but also is up against many core technologies to be solved.

4) The core technology has not been solved yet that developing a reduced-order model for gas-path fault with strong generalization ability, high accuracy, fast and low cost.

5) No matter any advanced sensor is adopted, the impact of incomplete and uncertain measurement data cannot be overcome.

Furthermore, it is not possible to gain the gas-path characteristic parameters of the whole flow field at various moments that is due to the limitation of engine design requirements and sensor installation conditions, especially for the fault monitoring of local small gas-path components, which still faces enormous challenges. And the data processing is time-consuming and labor-consuming, which makes use of the current PHM technology, and it is unable to efficiently to predict the gas-path health status of the engine[5]. Therefore, the current research status of the gas-path fault diagnosis technology is reviewed in this paper, it proposes a fault diagnosis method based on the fusion of CFD numerical simulation and machine learning, meanwhile, it is prospected that challenge and development trend of the gas-path fault diagnosis methods.

RESULTS AND DISCUSSION

1 RESEARCH PROGRESS OF GAS-PATH FAULT METHODS

1.1 Introduction to aero-engine gas-path fault diagnosis technology

In 1972, Urban[6] first proposed the gas-path fault diagnosis of aero-engine. In order to solve the problem of the disproportional relationship between engine state parameters and independent parameters, the nonlinear fault model was simplified to a linear mathematical model. Passalacque put forward an improved Kalman filter (KF) linear model for gas-path fault diagnosis in view of the shortcomings of the linear mathematical model method[7], such as neglecting the processing of sensor deviation and noise characteristic parameters and over-reliance on linear assumptions.

Zadda implemented nonlinear GPA fault diagnosis using an iterative method in 1995. It not only improves the prediction accuracy, but also solves the nonlinear relationship problem between the measured physical parameters and known parameters. Singh came up with the fault map method in 1996[8], which overcomes the problem of missing measurement parameters and measurement uncertainty to a certain extent.

Cui[9] et al. fused the collected multiple gas-path parameters information and genetic algorithm, which improved the evaluation accuracy. Pedro H. S. Calderano[10] used the steepest descent method to detect and classify gas turbine faults, and found this technology had high accuracy. Huang[11] et al. used the Bayesian feedback cloud model to analyze engine performance parameters and the relationship between the gas-path performance parameters of the evaluation model and the data collected by the sensor, which realizes the health state evaluation of the engine gas-path components.

In the 1980s, it was proposed that based on electrostatic induction engine gas-path fault on-line monitoring and diagnosis technology, the healthy condition of the engine was judge by charged particles the change law of abnormal signal the monitoring gas-path system. Thus, it could provide early warning capabilities of gas-path system fault, it does not need a lot of disassemble or change the engine gas-path components location layout. As long as the electrostatic sensors and signal processing equipment are installed at specific locations, online monitoring of engine gas-path faults can be realized, which effectively expands the range of engine gas-path fault early warning and improves the evaluation accuracy of fault diagnosis[12,13].

With the rapid development of artificial intelligence technology, some scholars use artificial neural network technology to effectively solve the contradiction between the number of engine measurement parameters and type of fault. Lombard[14] successfully applied back propagation network (BP) algorithm to the fault diagnosis of gas turbine engines in 1995. The Australian Aerospace Navigation Research Laboratory took advantage of the probabilistic neural network (PNN) fault diagnosis method and carried out a lot of experimental verification in the F404 turbofan engine[15]. The artificial neural network (ANN) was used to explore the noise signal and bias ability of the sensor in Ref.[16], then to be proposed that a series of diagnostic methods as antagonizing neural network and improving BP neural network[17].

In 2001, NASA Green Research Center installed multiple sensors of pressure, temperature, speed and turbulence intensity on C-17 transport aircraft, and it used information data fusion method to carry out fault diagnosis and analysis on the acquired characteristic data[18]. Chen[19] and Yuan[20] had successfully applied artificial neural network and Dempster/Shafer (D-S) evidence theory method to aero-engine gas-path fault diagnosis technology. In 2016, a fault diagnosis method based on kernel principal component analysis and wavelet neural network (KPCAWNN) was proposed in Ref.[21], which was used to simulation analysis on training data and test data, it is found that this method has good application value at the same time.

1.2 Development of the fusion method of CFD simulation and machine learning

So far the following three major research methods are used in the widely researched aircraft engine gas-path fault diagnosis technology based on machine learning the domestic and overseas scholar. The commonly used methods for the prediction of aero-engine gas-path parameters are shown in Figure 1.

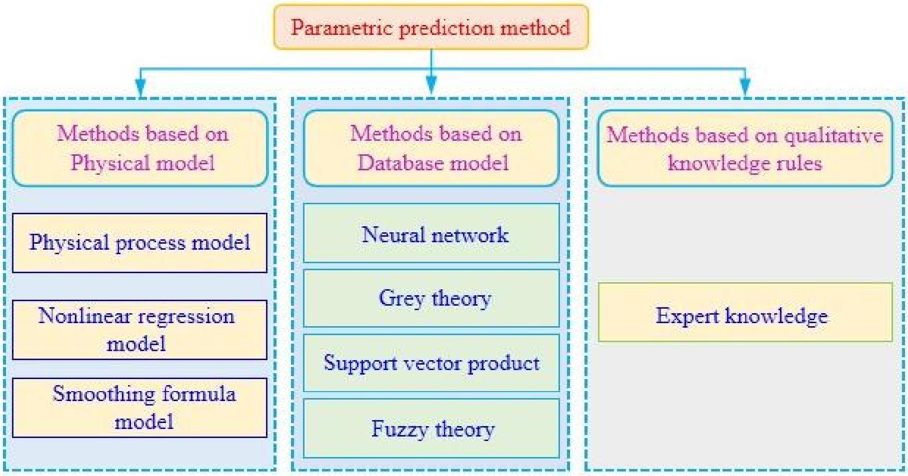

Figure1 Common methods of aero-engine parameter prediction

Model-based method refers to the establishment of a quantitative mathematical model of an engine. It is only suitable for information sufficient systems that can be modeled and have sufficient sensors, and this requires sufficient understanding of the mechanism and structure of the engine working process. Nowadays the typical approaches include physical processes, nonlinear regression and smoothing formulas and so on. In the use process, due to the strong non-linearity of the engine gas-path fault, the generalization ability and accuracy of the acquired gas-path fault model are poor[22].

The data-driven method is to make use of the characteristic parameters of the gas-path system for research in Ref.[23], which is suitable for databases containing huge amount of information and it is a method that with the most research and the most extensive application as well. The common methods mainly include, for instance, artificial neural network (ANN), grey theory, support vector machine (SVM)[24,25]and fuzzy system, etc. Practice has proved that SVM could solve nonlinear high-dimensional space problems through a small number of samples by using statistical theory, which has high generalization. ANN[26]could automatically find hidden feature information from big data, and it can directly process the original form of data to obtain experience or knowledge, and then it predicted the future behavior of complex nonlinear systems. ANN and SVM algorithms have a great potential in the field of gas-path fault diagnosis.

The method based on qualitative knowledge depends on the complete repository of the system, and it is suitable for the information deficiency system where the mathematical model cannot or is not easy to be established and the sensor information is insufficient. The expert system is currently the main method. It does not need to set up an accurate model, but it directly introduces the characteristic parameters and integrates them into the expert knowledge and experience in the engine field. However, it is a qualitative reasoning and prediction method, but it is unable to make quantitative prediction, for example, there are defects that difficulty in acquiring knowledge, incomplete knowledge, poor adaptability, etc. so its development is limited[27]. There were three methods of the advantages and disadvantages, which is notable in Table 1.

Table 1 comparison of gas-path fault diagnosis methods

Method	Predict object	Prediction accuracy	Disadvantage	Application scenarios
Methods based on Physical model	Governing equations of flow field and components	general	Generalization ability and accuracy is poor	Ground test and Off-line analysis
Methods based on Database model	Physical equations or a large number of flow field data	better	Mass of data	Ground test and flight
Methods based on qualitative knowledge rules	Small amount of flow field data	better	Qualitatively impossible to predict	Ground test and Off-line analysis

2 GAS-PATH FAULT DIAGNOSIS METHED BASED ON CFD SIMULATION AND MACHINE LEARNING

Up till now, the gas-path signal data of engines that support machine learning worldwide are basically derived from sensors. However, the accurate location and faults type determination of gas-path faults depend on the accuracy of data collected by sensors. And on account of the extremely complex and harsh working environment of the aero-engine gas-path system, which has brought severe challenges to the installation and performance of the sensor. In the meantime, it is a challenge that the feature extraction of the gas-path signal data by sensor. In short, the gas-path data collected by sensors may not reflect the real engine performance parameters, and it requires vast financial support to the experiment in this field. Therefore, a gas-path fault diagnosis technology based on the fusion of CFD simulation and machine learning is proposed.

2.1 Development of CFD simulation in gas-path fault diagnosis

As yet, the numerical simulation of aero-engine gas-path based on CFD mainly includes the simulation of pure flow field, fluid-solid two-phase flow, fluid-solid thermal multi-physics field and fluid-solid electric multi-physical field. It was calculated and simulated the overall flow field of a certain type of elastic engine in Ref.[28], and the working conditions of the whole engine flow field were obtained through mesh splice, dynamic mesh technology, turbulence model and engine working theory. The FLoEFD software was used to do the three-dimensional (3D) numerical simulation research on the overall KJ66 turbojet engine in Ref.[29], the distribution law of Ma, pressure and temperature of the whole engine is obtained, it establishes a relatively complete 3D machine performance research system to provide technical support and ideas for the machine numerical simulation research. Aero-engine gas-path system of gas-solid two phase numerical simulation was mainly single channel and multi-channel rotor blade and static blades, Zeng[30]et al. adopted two guide blades and four rotors of the 3D model, which the temperature and the blade impact characteristics was studied different size particles in the turbine flow passage along, and it is established the control equation that neglected the Centrifugal force and Coriolis acceleration, etc. Simultaneously, the particle Stocks number was introduced to describe the flow characteristics of the particle in the flow field. Zhang[5]did the relevant research, this was gas-solid-electric multi-physical field coupling field in the nozzle, its principle was through the gas-path system of charged particles the size of the abnormal charge to provide the basis and evaluation criteria for health status assessment. Hence, it played a conclusive role of the movement rule of gas-solid two phase flow of the gas-path system for the electrostatic monitoring technology. In China, the numerical simulation of gas-particle two-phase flow in the gas-path system of aero-engine is usually the simulation between the turbine and the outlet of the tail nozzle or between some channels of the turbine blade[5], there were few simulation study on gas-particle two-phase flow that considering turbine blades and the tail nozzle.

Up to now, scholars had not considered the influence of vortex and radial centrifugal force of turbine rotor on particle motion law in numerical simulation of gas-solid two-phase flow in aero-engine internal flow field, and no one adopted machine learning to obtain the corresponding reduced order model for the 3D gas-solid two-phase flow of particle flow and flow field variation rule of the engine in China. With the rapid development and application of artificial intelligence fault diagnosis, rotating machinery[32] and flow field simulation. The method and principle will be applied to the aero-engine gas-path fault diagnosis technology, the particle flow characteristics of gas-solid two-phase flow in the engine internal flow field are extremely complex, nevertheless. Up till now, the research method which can accurately reflect the particle flow characteristics is based on the CFD numerical simulation method. However, CFD numerical simulation is time-consuming but not fit for the on-line monitoring and fault diagnosis of engine gas-path faults. So that the advantage of it was got the utmost out of the accurate prediction the characteristic parameters the gas-solid two-phase flow of the engine through machine learning, the health status of the corresponding components the engine was judged by the change rules the flow field. Hence, the reduced-order model, once the machine learning algorithm network based on flow field simulation characteristics parameters has been trained successfully, it will save calculation time and resources in the practical application. So it is a strong application background and technical requirements that a reduced-order model making use of machine learning methods of gas-solid two-phase flow characteristics for online monitoring and health management technology of engine gas-path faults.

2.2 Gas-path fault diagnosis method based on the fusion of flow field simulation and machine learning

In view of this, it is a problems that incomplete test data and unclear movement law of gas-particle two-phase flow in aero-engine, at present, only the gas-particle two-phase flow in the turbine passage or in the tail nozzle is studied separately, this research group proposed the CFD simulation of gas-particle two-phase flow in the aero-engine with the combination of turbine rotor blade and tail nozzle. There is no doubt that the CFD numerical simulation method can have the data of the entire flow field at arbitrary time. It breaks the shortcoming of collecting data of partial gas-path system only by sensor for a long time. Firstly, a 3D model of micro-turbojet engine with turbine rotor is established and a structured grid is divided. Secondly, there are the pure flow field under corresponding working conditions by calculating that different temperature, pressure, speed and turbulivity etc. Then, it is calculated corresponding working conditions that gas-particle two-phase flow field with diverse particle size, velocity, temperature and material, and the movement and flow field parameters of particles under various conditions are obtained, the feature parameters are extracted and grouped at the same time. Subsequently, by referring to the relevant machine learning algorithm, the machine learning method is used to train above part of the flow field data. During the training, the first step is to train a Particle trajectory reduced order model under variable working conditions. For example, if the temperature changes, the pressure, the speed, the turbulivity and other working conditions remain unchanged, the second step is to train the Particle trajectory reduced order model corresponding to variable working conditions. so as to get the particle trajectory reduced-order model representing the movement law of gas-solid two-phase flow field in the case of gas-path fault, meanwhile, it is calibrated of the reduced-order model that another part of simulation result. Eventually, the healthy state of the engine is judged by the variation range of the parameters, which the required engine gas-path flow filed parameters is directly used to acquire of the particle trajectory reduced-order model, and the fault location and fault type can be easily, quickly and accurately obtained by the particle distribution location and distribution concentration. It is applied to the on-line monitoring and diagnosis that aero-engine gas-path faults. The technical route adopted in this project is shown in Fig.2.

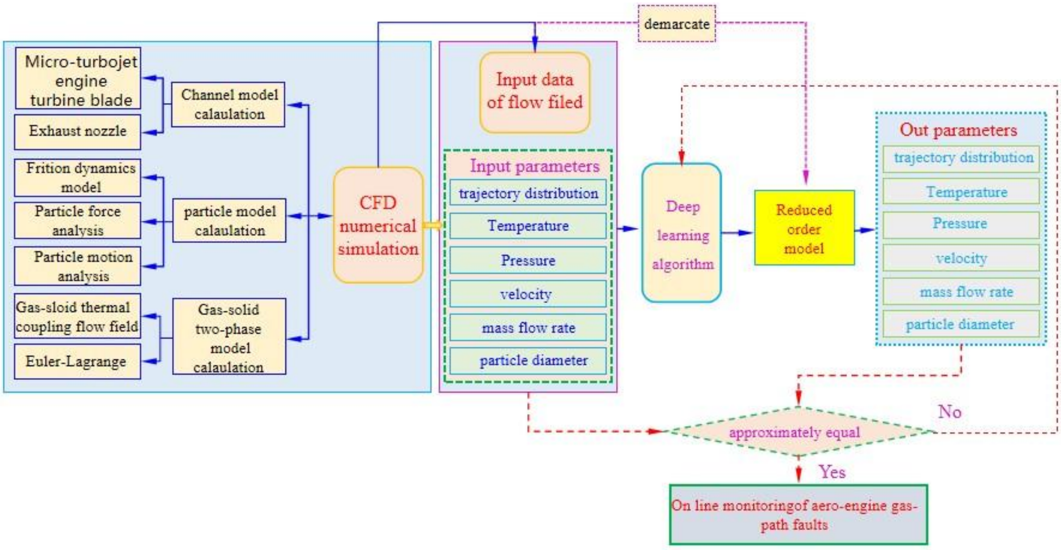

Figure 2 Technical route of fusion of flow field simulation and machine learning

In addition, he solution of hydrodynamics problems based on machine learning techniques usually follows the following steps: Firstly, we should make clear the extraction and type of gas-path characteristic parameters. Secondly, it is determined that theoretical relationship between the form of input and output and characteristic variables, when adopting machine learning method. Then, the network structures are designed according to the different goal parameters distribution forms, the corresponding network structure and activation function are designed, which determined to make fault reduced-order model with strong generalization ability and high precision. Next, the machine learning algorithm is determined, meanwhile, the corresponding loss functions and training process are designed, and the network structures and parameters setting are adjusted by means of the verification results and training model. Thus, we get the ideal algorithm network structure. Finally, the algorithm network application interface is designed so that it's practical application. A flow chart for based on machine learning to predict the motion law of flow field, which is shown in Fig.3.

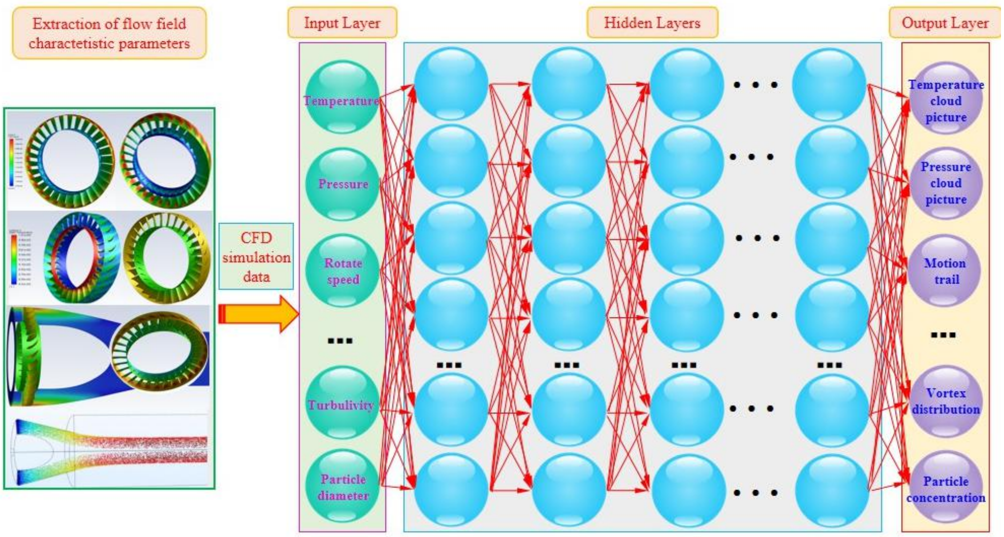

Figure 3 Computational flow field diagram based on machine learning to predict flow field motion law

2.3 Technical challenges in the fusion of flow field simulation and machine learning

1) Challenges of computational grid generation technology

According to the survey, high-quality grid generation accounts for 60% -70% of the whole CFD simulation cycle. Now, however, the topology division of structural grid is extremely complex, and the generation technology of unstructured grid and corresponding boundary layer is very time-consuming and difficult, which is still a challenge to the high-quality grid division of complex gas-path system. In addition, in which the CFD numerical simulation is carried out on the whole gas-path system, it involves the static field and the motion field, so it is difficult to merge the grids between the flow fields as well. It is still the bottlenecks of flow field simulation of gas-path system that the grid generation and adaptive technology. Since 2015, American Institute of Aeronautics and Astronautics (AIAA) has organized seminars that future grid generation technology and adaptive technology for many times. In 2016, NASA CFD Vision 2030 proposed the reconstruction of adaptive grid[33]. Sandia National Laboratory of geometry and mesh generation workshop has been held the roundtable on grid generation in 2017 and 2019.

2) Better type of machine learning algorithm

There are various machine learning algorithms supporting gas-path fault diagnosis, which has its own advantages so far. How to choose an algorithm suitable for describing gas-path fault reduced-order model is facing a huge test. This requires learning from experience and repeated training. It is a huge challenge to train some gas-path fault reduced-order model that can characterize the actual working conditions as far as possible.

3) Construction of high fidelity flow field database

Machine learning training gas-path fault reduced-order model relies on a large number of flow field simulation results to construct database. If we want to obtain a high precision and strong generalization ability of the reduced-order model by machine learning methods, we will need to show a huge amount of real working condition of CFD simulation data, so the structure of the boundary condition of simulation put forward higher request, hence, the structure of the high fidelity flow field data of machine learning training model and calibration of the model has a vital role.

4) Strong model generalization ability

It is still a great difficulty to train fault reduced-order model with strong generalization ability and high precision, on account of aero-engine gas-path fault parameters complexity and strong nonlinearity.

2.4 Technology Application

Engine gas-path fault diagnosis technology based on the fusion of flow field simulation and machine learning is playing an irreplaceable role in engine safety assurance and lower maintenance costs. It is mainly reflected in the following aspects:

(1) Through the gas-solid two-phase flow simulation data and machine learning algorithm of the engine gas-path system, which could be quickly and accurately located of the movement trajectory and distribution law of abnormal particles, it provided a new research method for the aero-engine gas-path electrostatic monitoring technology and breaks through the bottleneck problem of the electrostatic monitoring and fault diagnosis research at present .

(2) It was the reduced order model that may input immediately variable parameters, and then the location and type of fault is obtained fleetly and accurately. Furthermore, the cost of monitor maintenance and health management is reduced to a great degree.

(3) The reduced-order model of gas-path fault obtained by this technology, which can provide empirical data for sensor development and installation. Therefore, to a certain extent, the arrangement of sensors is optimized to obtain the engine gas-path more accurately and efficiently.

3 DEVELOPMENT TREND

Future research directions and development trends of machine learning diagnosis technology for aero-engine gas-path faults can be summarized as follows:

(1) Real-time. It provides timely feedback on the health status of complex gas-path systems, and the real-time diagnosis is needed to replace the existing periodic and itinerant diagnosis. So far it has been actualized partly to utilize sensors, yet there are still many challenges that to realize efficient real-time. Different machine learning algorithms are used for repeated training through a large number of data until the gas-path fault reduce order model reflecting the actual working conditions is trained, which can come true real-time in a certain sense.

(2) Model precision.The fault model trained by machine learning needs to consider various factors such as temperature, pressure, speed, height, material degradation performance and unexpected factors. Different machine learning methods are used for repeated training through a large number of data until the gas-path fault model reflecting the actual working conditions is trained.

(3) Intelligence. The engine gas-path system has the ability of self-diagnosis, self-prediction and self-adaptation. It can achieve rapidly and accurately self-diagnosis. That is, when in the absence of human intervention, it requires the training of reduced order model with strong generalization ability. Therefore, some functions of intelligent fault diagnosis will be improved to a large extent.

(4) Digital twinning. A novel research method has been proposed for aero-engine gas-path fault diagnosis and machine learning technology by aero-engine digital twin technique. By means of the physical model of high fidelity and the simulation data of multiple working conditions, some virtual model is reconstructed to simulate and predict the engine gas-path faults.

(5) Economization. It will bring down the test cost in significant measurement. In addition, it provides more accurate data for maintenance as well. Furthermore, it is the maximization of operating economic benefits.

CONCLUSIONS

In this contribution, the development of machine learning-based aero-engine gas-path fault diagnosis technology has been reviewed at present, which introduces the current main gas-path fault data-driven machine learning methods, and it summarizes the main problems existing in machine learning gas-path fault diagnosis methods and the core technologies to be solved.The development trend of the gas-path fault diagnosis technology based on the fusion of flow field simulation and machine learning for aero-engine is prospected, which conducive to objectively understand the current research status. And then some relevant insights are put forward that new methods and theories of aero-engine gas-path fault monitoring and diagnosis. Hence, it will require the joint efforts of academia and industry to realize this technology.

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REFERENCES

[1] Kurz R , Brun K , et al. (2009). Degradation Effects on Industrial Gas Turbines. *Journal of Engineering for Gas Turbines and Power*, 131(6), pp. 01-07.

[2] Li Y . (2017). Research on Fault Prediction and Health Management Method Based on Machine Learning. *University of Electronic Science and Technology of China*, pp. 01-72.

[3] Jiang L , Xu K, et al. (2002). Aero Engine Fault Diagnosis Technology Review. *Aeronautical Science and Technology*, 2(1), pp. 381-408.

[4] Jiang L , Li S , et al. (2005). Research Status of Gas Path Fault Diagnosis for Aero- Engine. *Journal of Civil Aviation University of China*, 3(4), pp. 52-60.

[5] Zhang H . (2019). Multi-field Coupling Model and Electrostatic Characteristics of Aero-engine Wake. *Rocket Force Engineering University of china*, pp. 01-78.

[6] Urban L A . (1972). Gas Path Analysis Applied to Turbine Engine Condition Monitoring. *AIAA Paper*, pp. 72-1082.

[7] Kobayashi T , Simon D L . (2007). Integration of On-Line and Off-Line Diagnostic Algorithms for Aircraft Engine Health Management. *Journal of Engineering for Gas Turbines and Power*, 129(4), pp. 649-659.

[8] Zedda M , Singh R . (2002). Gas Turbine Engine and Sensor Fault Diagnosis Using Optimization Techniques. *Journal of Propulsion & Power*, 18(5), pp. 1019-1025.

[9] Cui W , Ye Z, et al. (2015). Gas-path Fault Diagnosis of Aero-Engine Based on Information Fusion Genetic Algorithm. *Journal of Aerospace Power*, 30(5), pp. 1275-1280.

[10] Calderano P H S , Ribeiro M G C , et al. (2019). An Enhanced Aircraft Engine Gas Path Diagnostic Method Based on Upper and Lower Singleton Type-2 Fuzzy Logic System . *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, 41(2).

[11] Huang X , Li S , et al. (2014). Aero-engine Performance Evaluation Based on Bayesian Feedback Cloud Model. *Aeronautical Manufacturing Technology*, 451(7), pp. 94-98.

[12] Li Y. (2011). Research on Application of Electrostatic Induction Technology in gas -path Condition Monitoring of Aero-Engine. *Nanjing University of Aeronautics and Astronautics*, pp. 1-108.

[13] Powrie H, Novis A. (2006). Gas Path Debris Monitoring for F-35 Joint Strike Fighter Propulsion System PHM. *Aerospace Conference, 2006 IEEE IEEE*.

[14] Torella G, Lombardo G. (1995). Utilization of Neural -Networks for Gas-Turbine Engines. *1995XII ISABE95-703*.

[15] Ye Z , Sun J . (2002). Prospect of Gas Path Fault Diagnosis of Aero-Engine Based on Neural Network. *Journal of Propulsion Technology*, 23(1), pp. 278-285.

[16] Li I.Y. (2016). Performance Analysis Based Gas - Turbine Diagnostics: A Review, Proceedings of The Institution of Mechanical Engineers. *Journal of Power and Energy*, 216(5), pp. 363-377.

[17] Volponi A, Depold H, et al. (2000). The use of Kalman - filter and neural methodologies in gas - turbine performance diagnostics:a comparative study. *Journal of Engineering for Gas Turbines & Power* , 125(4).

[18] Allan J Volponi ,Tom Brotherton , et al. (2004). Development of an Information Fusion System for Engine Diagnostics and Health Management. *AIAA 1st Intelligent Systems Technical Conference 20-22 September 2004*.

[19] Chen T , Sun J G , et al. (2006). Neural network and Dempster-Shafter theory based fault diagnosis for aeroengine gas path. *Aeronautica et Astronautica Sinica*, 27(6), pp.1014-1017.

[20] Yuan C , Yao H. (2007). Performance Diagnosis of Aero-Engine Based on Kalman Filter and Genetic Algorithm. *Journal of Propulsion Technology*, 2007(01), PP. 9-13.

[21] Jian G, Cui, G, et al. (2019). Aero-engine Fault Diagnosis Based on Kernel Principal Component Analysis and Wavelet Neural Network.*//The 31st*

Chinese Conference on Control and Decision.
[22] Li Yongliang. (2017). Research on Fault Prediction and Health Management (PHM) Method Based on Machine Learning. *University of Electronic Science and Technology of China*,pp. 1-98.
[23] Ma J, Su H, et al. (2018). Predicting the Remaining Useful Life of an Aircraft Engine Using a Stacked Sparse Auto-Encoder with Multilayer Self-Learning[J]. Complexity, 2018, pp. 1-13.
[24] Capata, Roberto. (2016). An Artificial Neural Network-Based Diagnostic Methodology for Gas Turbine Path Analysis—part I: Introduction. Energy, *Ecology and Environment*, 1(6), pp. 343-350.
[25] Moura M C , Zio E , et al. (2011). Failure and Reliability Prediction by Support Vector Machine. *Reliability Engineering & System Safety,* 96(11),pp. 1527-1534.
[26] Shin H J, Eom D H, et al. (2005). One-Class Support Vector Machines—an Application in Machine Fault Detection and Classification.*Computers & Industrial Engineering*, 48 (2), pp. 395-408.
[27] Ding G , Fu X , et al. (2011). Aeroengine Performance Parameters Prediction Based on Process Neural Network. *Computer Integrated Manufacturing Systems*, 2011(01), pp. 198-207.
[28] Li T. (2019). Research on 3D Numerical Simulation of Micro Turbine Jet. *Dalian University of Technology*.
[29] Shen W, Xin Y , et al. (2011). Numerical Simulation of Flow Field for Small Turbojet Engine. *Aeronautical Computing Technology*, 2011(06), pp. 73-75.
[30] Zeng F , Song Y , et al. (2020). Study on Temperature of Particles with Different Sizes in Turbine Passage and Its Impact Characteristics with Blades. *Propulsion Technology*. 2020(8).
[31] Mitchell D A, Soliz M. (1974) Evaluation of Electrostatic Probe Technique for Detection of Particles Emitted during Turbine Engine Distress. 52(1).
[32] Min X , Teng L , et al. (2017). Fault Diagnosis for Rotating Machinery Using Multiple Sensors and Convolutional Neural Networks. *IEEE/ASME Transactions on Mechatronics*, PP(99):1-1.
[33] Yao S , Tang X , et al. (2017). Three-Dimensional Numerical Study of Flow Particle Paths in Rotating Detonation Engine with a Hollow Combustor0. *Combustion Science & Technology*, 189(4-6), pp. 965-979.