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Performance Degradation Evaluation of Low Bypass Ratio Turbofan Engine Based on Flight Data

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Abstract: A low bypass ratio turbofan engine operates in a hostile environment, resulting in performance degradation. This seriously affects the security and reliability of the engine. Therefore, a performance degradation evaluation method for engines based on flight data is proposed. The method expands the equation system to solve the underdetermined problem caused by the lack of engine sensors based on multiple operating point analysis. The improved evolution algorithm is employed to solve the equation system, which relieves the problem of insufficient precision. The engine performance degradation dataset is established based on the engine performance calculation model to verify the reliability of the degradation evaluation method. The results show that the method is applicable to the dataset. Finally, the method is applied to the actual flight data to study the law of the performance degradation of the researched engine, which indicates that the engine's fan efficiency and high-pressure compressor flow capacity have an apparent downward trend over time.

Keywords: performance degradation; flight data; multiple operating point analysis; differential evolution



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1. Introduction

Aero-engines work in complex environments, such as high temperature, high pressure, and high speed, for a long time. During the operation, problems such as blade erosion, fouling, and tip clearance inevitably occur, resulting in performance degradation [1,2]. Significantly, the operating state of the low bypass ratio turbofan engine is changeable, which causes more severe performance degradation. The degradation of engine performance is mainly reflected in the reduction of thrust, engine overtemperature, and increase in fuel consumption. They not only increase energy consumption but also affect the flight safety and reliability of the engine. Therefore, to ensure the safety and improve the sustainability of aero-engine, it is necessary to conduct research on the performance degradation evaluation of turbofan engines.

Performance degradation is usually characterized by components' efficiencies and flow capacities, which are called health parameters [3,4]. Performance degradation evaluation by estimating the health state helps condition-based maintenance, which benefits the safety of aero-engine and reduces use costs. Therefore, health state estimation has received more attention from scholars for decades. Aero-engine health state estimation methods are mainly divided into model-based and data-driven methods [5].

Model-based methods estimate health parameters based on deviations of engine sensor data from accurate engine performance calculation models. In the 1970s, Urban [6] introduced a gas path analysis method to isolate single or multiple engine faults through a fault coefficient matrix. However, the number of engine sensors is limited due to installation space and weight. This results in the phenomenon of fault diffusion in the estimation results. To solve the problem that the number of sensors was less than the types of engine faults, Stamatis [7] and Gulati [8] proposed the multiple operating points analysis (MOPA) method, which solved this problem by selecting multiple steady-state points to expand the

equation system. However, this method requires that the selected steady-state points have a particular difference to avoid the multicollinearity effect of the fault coefficient matrix. Sampath et al. [9] used a genetic algorithm to conduct fault diagnosis research on engines considering sensor noise. At the same time, algorithms such as the Kalman filter [10], extended Kalman filter [11], and unscented Kalman filter [12] were also widely used in engine gas path fault diagnosis research. It had certain advantages in dealing with sensor noise but required specific degenerate prior knowledge.

With the continuous development of data processing technology, data-driven methods have received more extensive attention from scholars. The method did not need to consider the actual working principles of the engine and the aero-thermodynamic process. Training a large number of “measured parameters-health parameters” mapping samples can calculate the engine performance degradation trend from the measured parameters. The long-short-term memory network [13–15] can deeply mine the characteristics of time series and alleviate the gradient disappearance and gradient explosion problems of traditional recurrent neural networks. It also showed excellent predictive ability in the NASA C-MPASS aero-engine simulation dataset [16].

However, some of the above theoretical algorithms are still far from practical engineering applications. On the one hand, the number of sensors installed in actual turbofan engines is limited, and it is difficult to obtain a large number of “measured parameters-health parameters” mapping samples, which makes it challenging to apply data-driven methods to practical work. On the other hand, the measurement noise of engine sensors is difficult to satisfy the Gaussian distribution, and it is difficult to obtain accurate prior knowledge of degradation, making the Kalman filter algorithm challenging to apply to actual engine degradation evaluation research.

This paper proposes a degradation assessment method based on the characteristics of engine sensors. The novelty of the method lies in the reasonable assumption that it converts an underdetermined problem into a positive definite problem. A novel fitness function considering sensor noise and model error is proposed. The method can be applied to actual flight parameter data, and the degradation law of the researched engine is obtained. First, the method constructs a fitness function using the difference between the engine measurements and the engine model. At the same time, weights are introduced into the fitness function to consider the influence of sensor measurement noise and model errors. Second, given the problem of insufficient measurement parameters in the traditional health parameter estimation method, the method adopts the multiple operating point analysis (MOPA). By introducing multiple operating points to expand the health parameters to solve the equation system, it solves the underdetermination in the nonlinear equation system solution. Finally, the improved differential evolution algorithm is applied to solve the health parameters inversely to solve the problem of insufficient precision in parameter estimation.

To verify the effectiveness and reliability of the proposed method, this paper establishes a simulation dataset for engine performance degradation with injected degradation trends. It provides a basis for practical engineering applications by performing calculations and verifying the dataset. The method is then applied to the actual flight parameter data to estimate the performance degradation trend of each component of an engine under actual flight conditions. The study not only shows the degradation law of the researched turbofan engine but also provides a basis for the scientific, rational, and efficient use of the engine.

2. Methods

2.1. Problem Description

The researched aero engine is a low bypass ratio turbofan engine, which is mainly composed of the fan, compressor, combustor, high-pressure turbines, and low-pressure turbines. There is a complex coupling relationship between these components [17]. Studies [18] have shown that the performance degradation of the engine is mainly reflected in the change in the component structure (such as blade tip drop, blade corrosion, etc.) and that the performance is manifested in the change in the air path characteristics (flow

capacities and efficiencies) of the rotating parts. Therefore, the health parameters for the flow capacities and efficiencies of the rotating components of the engine are usually defined as follows:

$$SW = \frac{W_d}{W_c} \quad (1)$$

$$SE = \frac{\eta_d}{\eta_c} \quad (2)$$

where SW is the flow capacity of components, SE is the efficiency capacity of components, W is the conversion flow of components, η is the efficiency of components, the subscripts d is the degraded engine data, and c is the clean engine data.

Usually, the nonlinear aerodynamic thermodynamic model of an aero-engine considering the degradation of component performance can be expressed as follows:

$$z = g(\mathbf{u}, \boldsymbol{\theta}) \quad (3)$$

where \mathbf{u} is the engine input vector, z is the engine measurement parameter vector, and $\boldsymbol{\theta}$ is the vector composed of the performance health parameters (SW and SE) of each rotating component of the engine.

Since the health parameters of components cannot be directly measured or calculated from sensor measurement parameters, the performance degradation evaluation of aero-engine gas path components is essentially an estimation problem of unmeasurable parameters. Usually, Equation (3) is solved inversely according to the measured parameters. The component health parameters are estimated as follows:

$$\boldsymbol{\theta} = G^{-1}(x, z) \quad (4)$$

However, the solution of the above formula needs to satisfy that the number of measurement parameters is more than or equal to the number of health parameters. The number of actual engine sensors is limited by installation space and weight. It is difficult to meet the requirement, making the above equation's solution an underdetermined problem. The equation cannot be solved theoretically.

2.2. MOPA Application Based on Flight Parameter Data

Aiming at the above underdetermined problem, Stamatis [7] proposed the MOPA, which assumes that the health parameters of each component remain unchanged during a single flight cycle. It expands the solution equations for the health parameters by selecting multiple steady-state operating points to solve the problem of insufficient measurement parameters. It requires a certain independence between the selected steady-state operating points to alleviate the multicollinearity problem in the solution of the health parameters. However, Diakunchak [19], Aker and Saravanamuttoo [20] pointed out that the degradation degree of flow capacities and efficiencies will change with the operating points due to different aerodynamic conditions. This contradicts the assumption that the health parameters of each steady-state operating point of the MOPA are equal. In order to reduce the error resulting from the MOPA assumption, it is necessary that the difference between each operating point be as small as possible when selecting multiple operating points. Therefore, the choice of multi-operating point states is a paradoxical issue when applying MOPA.

It was found that the steady-state operating point of the researched engine is mainly concentrated in a small high-pressure spool speed range (86–92%) by analysis of the actual flight parameter data. Since this speed range is small, the aerodynamic characteristics of multiple operating points can be approximated to be the same. Furthermore, the component performance health parameters of multiple operating points in the small range can be approximately considered equal. At the same time, to alleviate the multicollinearity problem in the solution of the equation system, a steady-state operating point with a significant difference in the speed range should be selected as much as possible during the calculation.

Aiming at the above problems, this paper transforms an equation system that solves the problem of Equation (4) into an optimization problem. It solves engine health parameters by minimizing the fitness function. It then uses an improved differential evolution algorithm to solve the optimization problem.

The MOPA method is used in the area to expand Equation (4):

$$\begin{cases} \theta = G^{-1}(x_k(t), u_k(t), z_k(t)) \\ x_k(t) = [x_1^T, x_2^T, \dots, x_q^T]^T \\ u_k(t) = [u_1^T, u_2^T, \dots, u_q^T]^T \\ z^k(t) = [z_1^T, z_2^T, \dots, z_q^T]^T \end{cases} \quad (5)$$

where q is the number of operating points selected by the MOPA.

The fitness function of this optimization problem is defined as follows:

$$OF = \sqrt{\frac{\sum_{i=1}^q \sum_{j=1}^p \left(\frac{Y_{ij}^m - Y_{ij}^{cal}}{Y_{ij}^m} \right)^2}{p \times q}} \quad (6)$$

where Y_{ij}^m is the j th actual measured parameter value of the i th operating point, Y_{ij}^{cal} is the calculated parameter value of the j th model of the i th operating point, and p is the number of the aero engine sensors.

Equation (6) does not consider the influence of engine model error and sensor measurement noise. Since the aero-engine is a complex aerodynamic thermodynamic system, a series of assumptions in the model cause calculation errors in the physical model. At the same time, the complex flow field inside the engine makes it difficult for the measured value of the engine sensor to represent the actual value of the entire section, resulting in measurement noise from a certain sensor. Therefore, to improve the accuracy of health parameter estimation, it is necessary to consider the influence of model error and sensor measurement noise. The standard deviation of the measurement parameters is used as the weight and added to the fitness function [18]. At this time, the fitness function becomes:

$$OF = \sqrt{\frac{\sum_{i=1}^q \sum_{j=1}^p \left(\frac{Y_{ij}^m - Y_{ij}^{cal}}{Y_{ij}^m \cdot \sigma_j} \right)^2}{p \cdot q}} \quad (7)$$

where σ_j is the standard deviation of the j th measurement parameter.

In practical work, due to sensor characteristics, the measurement noise of aero-engine sensors is difficult to satisfy the Gaussian distribution. Figure 1 shows the noise distribution of a certain type of engine thermocouple for multiple measurements of the same temperature. It can be seen that the actual sensor measurement noise is quite different from the Gaussian distribution.

In addition, due to the inaccuracy of the characteristic map of engine components, the calculation error of the parameters measured by the engine performance calculation model may also deviate from the Gaussian distribution. Figure 2 shows the engine performance model's calculation error distribution of the exhaust temperature. It is not exactly a Gaussian distribution.

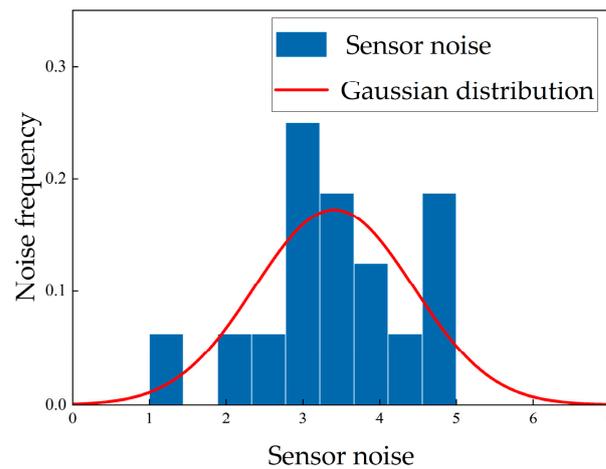


Figure 1. Sensor noise distribution and its Gaussian distribution.

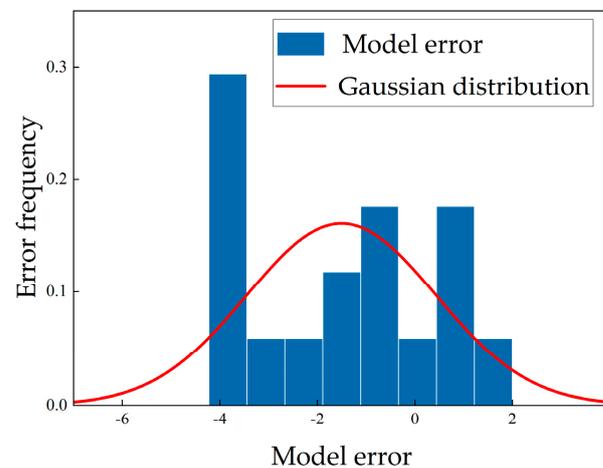


Figure 2. Model error distribution and its Gaussian distribution.

The actual engine sensor technical specification has an error range for the measurement parameter. Therefore, this paper comprehensively determines the weight of the parameter according to the relationship between the noise range of the measurement parameter and the model error and brings it into the fitness function. Then, the improved fitness function is:

$$OF = \sqrt{\frac{\sum_{i=1}^q \sum_{j=1}^p (\omega_j \cdot \frac{Y_{ij}^m - Y_{ij}^{cal}}{Y_{ij}^m})^2}{p \cdot q}} \quad (8)$$

where ω_j is the weight of the j th measurement parameter.

Affected by sensor measurement noise, the selection of the number of operating points also requires attention. Usually, the larger the number of selected operating points, the more redundant the data and the more accurate the solution of the health parameters. However, when there are engine sensor errors, the more data there are, the more difficult it is for the solution of the engine health parameters to converge. This results in the “smearing” phenomenon (the performance degradation of one component may be reflected in another component). The health parameter calculation tends to the direction of the noise disturbance changes.

Therefore, to reduce the influence of noise as much as possible, the number of operating points should be selected as small as possible while satisfying the MOPA calculation conditions. In general, to ensure that the system of equations can be solved, the number

of operating point selection should satisfy $p \times q \geq n$. Additionally, q is the smallest value that satisfies inequality. In particular, the researched engine is equipped with five gas path sensors, which are high-pressure spool speed (N_1), low-pressure spool speed (N_2), total pressure at high-pressure compressor outlet (P_{t3}), total temperature at low-pressure turbine outlet (T_{t5}) and fuel flow (W_f). W_f is the input of the performance calculation model, and the output of model p is 4. The number of health parameters, n , is 10. To make sure, the number of multi-operating points q selected is 3.

The traditional genetic algorithm is prone to severe “smearing” in the solution, and the calculation accuracy is poor. Therefore, this paper adopts an improved differential evolution algorithm named JADE [21], which improves convergence and robustness by adaptively adjusting control parameters. JADE improves the “smearing” phenomenon to a certain extent.

JADE is based on the improvement of the differential evolution algorithm. The differential evolution algorithm is an optimization algorithm based on swarm intelligence theory [22]. It achieves global search optimization through mutation, crossover, and selection operations. Because the algorithm has the advantages of few control parameters, high optimization accuracy, strong global search ability, and easy engineering applications, it is widely used in many real-world optimization problems [23,24]. However, since calculating the health parameters takes a lot of time, the optimal control parameters scaling factor and crossover rate cannot be selected by statistical methods. Therefore, this paper uses the adaptive differential evolution algorithm JADE to adjust the control parameters to ensure that the control parameters are always optimal.

At the same time, the algorithm introduces a new mutation strategy DE/current-to-pbest based on the mutation strategy DE/current-to-best, which utilizes the information of the optimal solution and other optimal solutions information. The difference between the archived inferior solution and the current population can be incorporated into the mutation operation. The population has diversity and can alleviate problems such as premature convergence. Compared with the standard evolutionary algorithm, the method reduces evolutionary generation while ensuring robustness.

The specific health parameter calculation process is shown in Figure 3.

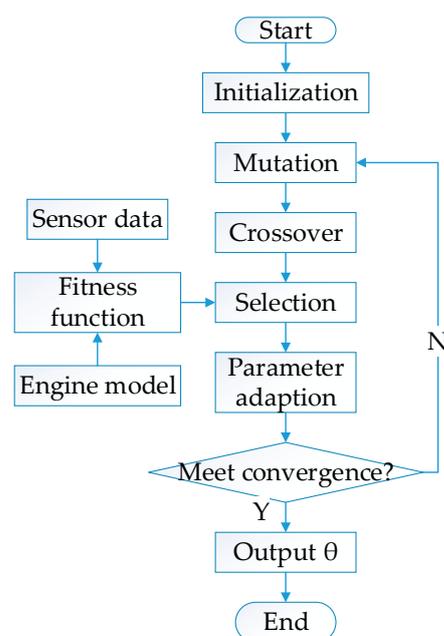


Figure 3. Flowchart of health parameter calculation.

2.3. Creation of Degradation Simulation Dataset

To verify the reliability of the proposed method under the influence of sensor measurement noise, a performance degradation dataset of the researched turbofan engine is established in this paper. To make the dataset truly reflect the actual degradation, the degradation law consistent with NASA's C-MPASS aero-engine simulation dataset [16] is adopted. The initial degradation and final value degradation are shown in Table 1. During the degradation process, the exponential degradation rate is applied to the health parameters of each component, and the expression is as follows:

$$\theta_k(t) = 1 - d_k - \exp(a_k t^{b_k}), k = 1, 2, \dots, 10 \quad (9)$$

Table 1. Initial value and final value of health parameters.

Health Parameters	Initial Wear (%)	Final Wear (%)
SE12 (fan efficiency)	−0.18	−2.85
SW12 (fan flow)	−0.26	−3.65
SE2 (low-pressure compressor efficiency)	−0.50	−2.65
SW2 (low-pressure compressor flow)	−0.80	−3.58
SE26 (high-pressure compressor efficiency)	−0.62	−2.61
SW26 (high-pressure compressor flow)	−1.01	−4
SE41 (high-pressure turbine efficiency)	−0.48	−2.63
SW41 (high-pressure turbine flow)	0.08	2.57
SE46 (low-pressure turbine efficiency)	−0.10	−1.08
SW46 (low-pressure turbine flow)	0.08	0.42

A dataset of the health parameters is generated using Equation (9) over time. The health parameters are the input vector of the engine performance model. At the same time, the steady-state operating points of the speed range mentioned above in the entire life cycle of the researched engine are extracted, and three steady-state points with significant differences in the operating state within a single flight sortie are screened. The engine operating and flight conditions from the actual dataset are used as input vectors to the model. A random error within the measurement error range of the sensor is added to the output of the model.

On the one hand, the input degradation of the dataset is similar to the possible degradation of the engine; on the other hand, the simulated operating point is consistent with the actual operating steady-state point of the engine, which can truly reflect the actual operating state of the engine. Therefore, the dataset can effectively validate the health parameter evaluation method proposed in this paper.

3. Results

3.1. Validation of the MOPA Method

In order to verify the validity and reliability of the proposed method, the degradation dataset without noise, and the degradation dataset with noise were calculated and verified, respectively.

Table 2 shows the two groups of randomly implanted health parameters and estimated values, and Figure 4 shows the estimated health parameters for the noise-free performance degradation dataset. The results in Table 2 show that the health parameter values estimated by the method have high accuracy.

Table 2. Implantation and estimation of engine health parameters.

Health Parameters	Example 1		Example 2	
	Preset Value	Estimated Value	Preset Value	Estimated Value
SE12	0.98	0.9814	0.99	0.9898
SW12	0.99	0.9897	0.97	0.9695
SE2	0.98	0.9784	0.99	0.9901
SW2	0.99	0.9903	0.97	0.9706
SE26	0.96	0.9615	0.99	0.9904
SW26	0.99	0.9897	0.97	0.9703
SE41	0.98	0.9786	0.99	0.9910
SW41	1.02	1.0197	1.03	1.0301
SE46	0.98	0.9797	0.99	0.9905
SW46	1.02	1.0200	1.03	1.0297

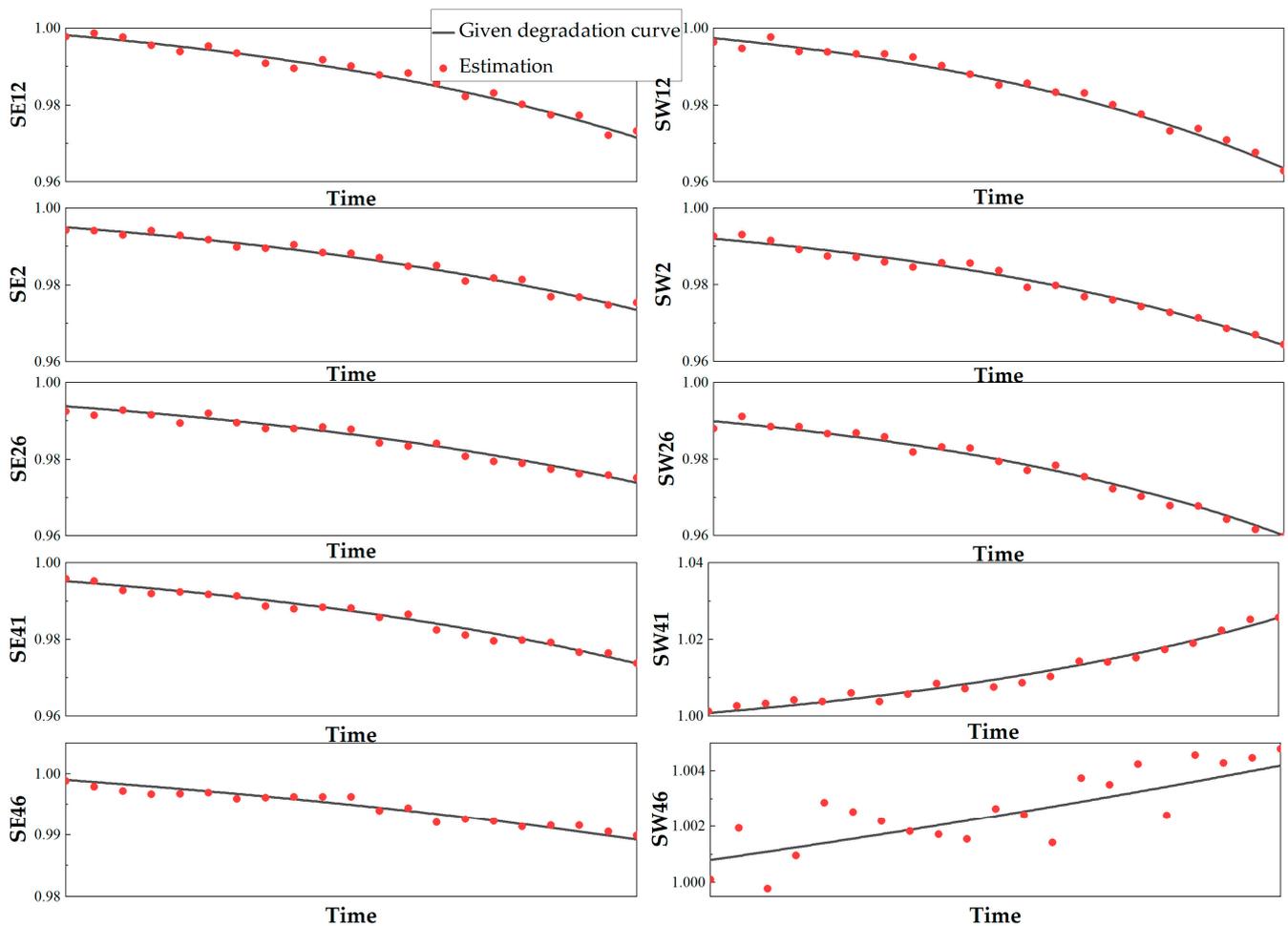


Figure 4. Health parameters for estimation under dataset without noise.

Figure 3 shows the estimation results of health parameters in the degradation process in the dataset without noise. The black lines are the given degradation curves, and the red dots are their estimates. The estimation results fit the given degradation index curve well. The accuracy of each point is within 0.3%, which can meet the needs of engineering accuracy.

For further validation, health parameter estimation calculations were performed on a dataset with noise. In the degraded dataset with noise, the multi-operating point measurement values of the MOPA method are all affected by random noise, and the assumption that the degradation values between the operating points are equal is affected to a certain extent. Therefore, the problem of poor convergence of some points in the solution of the equation

system will occur. The resulting estimation of the health parameters under the influence of noise is shown in Figure 5. The black lines are the given degradation curves, and the red lines are their estimates. Although the estimation accuracy of the health parameters is affected, the estimated curve can still reflect the trend of performance degradation, so it is further verified that the method can be used for performance degradation evaluation of actual flight parameter data.

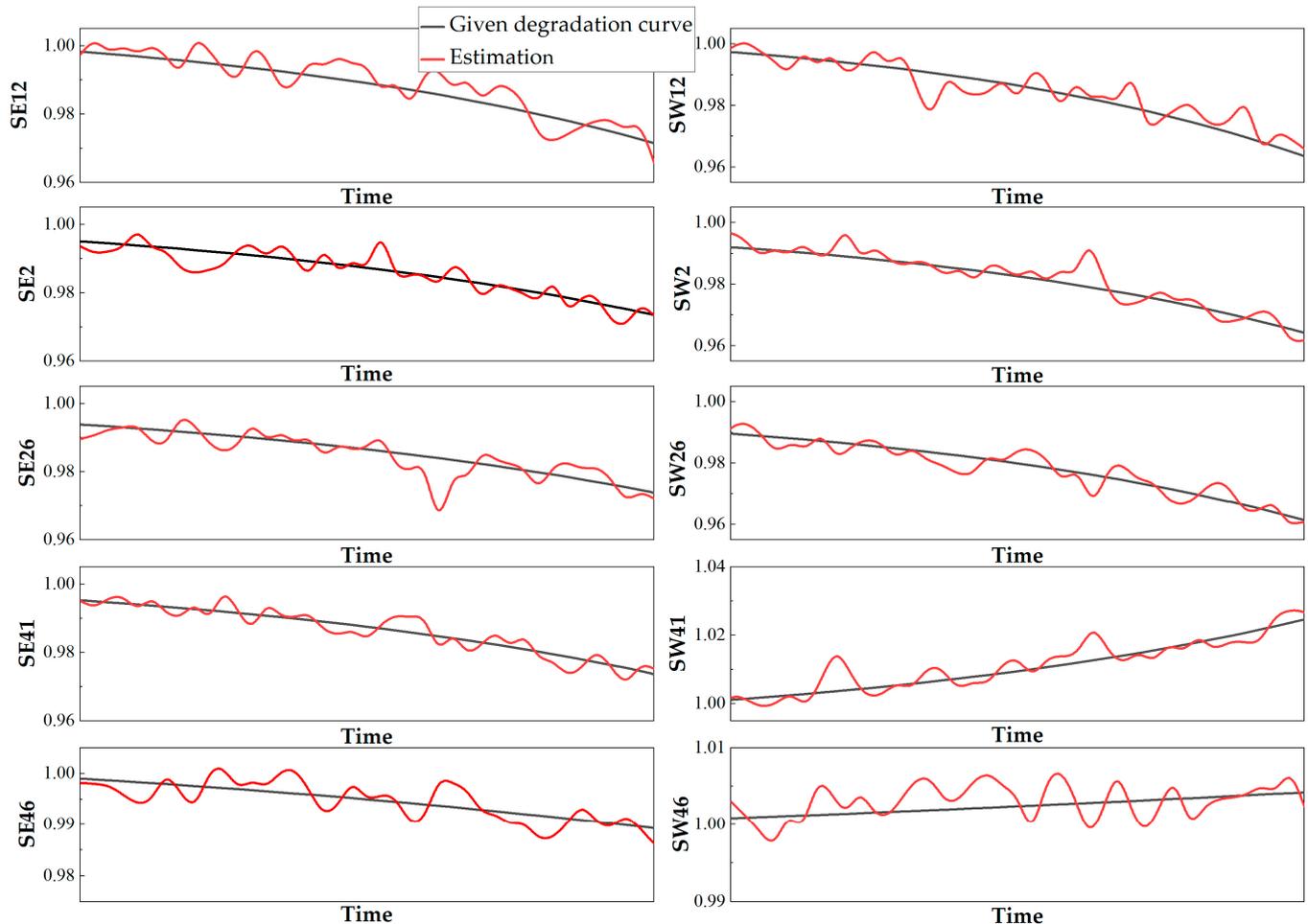


Figure 5. Health parameter estimation under dataset with noise.

3.2. Performance Degradation Evaluation of Actual Flight Parameter Data

In performance degradation based on actual flight data, the flight data of the new engine are taken as the ideal state that the engine has not degraded. The initial health parameters of the new engine are assumed to be 1, and the corresponding engine model is taken as the baseline model.

The actual flight parameter data of an engine is selected. This paper takes the steady-state point where the MOPA method is applicable. It uses the baseline model to calculate the fitness function value of each engine flight for a long period (Equation (8)), and the results are shown in Figure 6. With the increase in flight time, the fitness function shows an obvious upward trend, indicating that the performance of the engine components is increasingly different from the ideal state of the new machine. This means that this type of engine has an obvious performance degradation phenomenon during operations. It also shows that the method proposed in this paper is suitable for evaluating the performance degradation of actual engines.

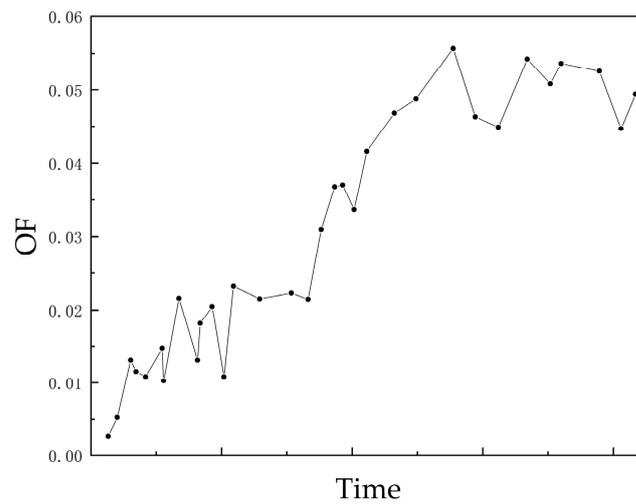


Figure 6. The fitness function value of an engine for a long time.

By estimating the degradation of the engine, the health parameter estimation curve is obtained, as shown in Figure 7, in which the fan efficiency and high-pressure compressor flow rate decrease obviously with time, and the maximum degradation amounts are 5.95% and 6.59%, respectively. Therefore, these components require special attention in actual maintenance.

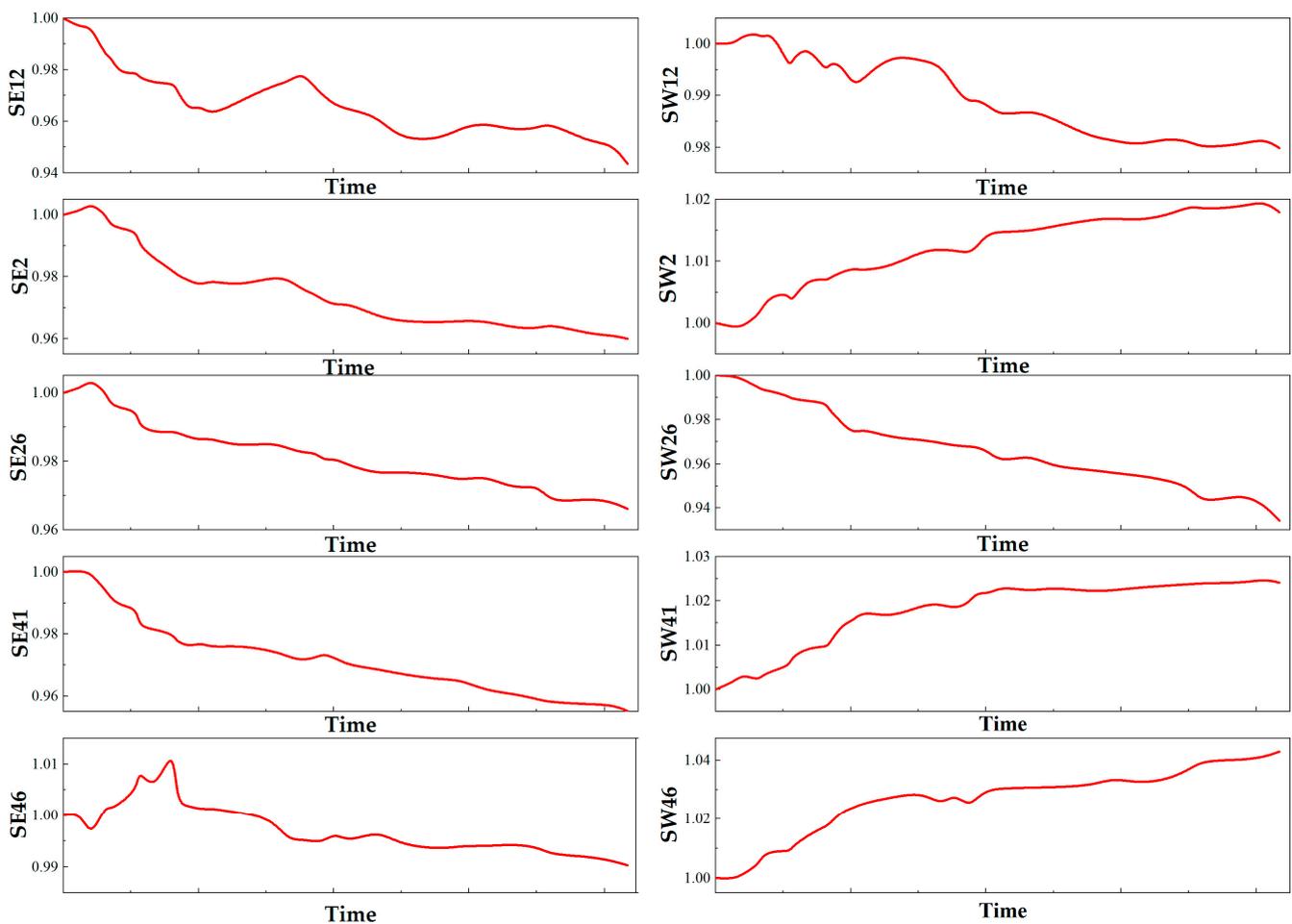


Figure 7. Health parameter estimation of an engine for a long time.

Due to factors such as manufacturing tolerance and different operating conditions, each engine has differences in the degradation trends of components. Therefore, it is necessary to combine the data of multiple engines to study the general law of performance degradation for the researched engine so that targeted maintenance measures can be taken in actual work.

4. Conclusions

A performance degradation evaluation method for a turbofan engine based on flight parameter data is proposed. The innovation of this paper is to solve the underdetermined problem of health factor estimation through reasonable assumptions. It expands the health factor to solve the equation system through multiple steady-state operating points. A novel fitness function considering sensor noise and model error is proposed. In this paper, the method is applied to actual flight parameter data, and the degradation law of the researched engine is obtained. One advantage of this method is that it does not require any priors and is not restricted by the condition that the available measurement number is less than the count of health factors. Another advantage of this method is that the estimation accuracy is better than that of the traditional genetic algorithm since an improved differential evolution algorithm is used to solve the above optimization problem.

The method is tested using the engine performance degradation verification dataset. The test and verification are carried out on the degradation dataset without noise and the degradation dataset with noise, respectively, which provide a basis for applying the method in actual engines. Finally, the performance degradation of the engine is evaluated. The research shows that the fan efficiency and high-pressure compressor flow rate of this engine have an obvious downward trend over time. Special attention should be paid to the components mentioned above, with obvious degradation in actual maintenance. Furthermore, the degradation evolution method can provide technical support for flight safety and improve engine operation reliability.

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References

1. Huang, J.; Wang, Q.; Lu, F. Research status and prospect of gas path fault diagnosis for aeroengine. *J. Nanjing Univ. Aeronaut. Astronaut.* **2020**, *52*, 507–522.
2. Volponi, A.J. Gas turbine engine health management: Past, present, and future trends. *J. Eng. Gas Turbines Power* **2014**, *136*, 051201. [[CrossRef](#)]
3. Lu, F.; Gao, T.; Huang, J. Nonlinear Kalman filters for aircraft engine gas path health estimation with measurement uncertainty. *Aerosp. Sci. Technol.* **2018**, *76*, 126–140. [[CrossRef](#)]
4. Hanachi, H.; Mechefske, C.; Liu, J. Performance-based gas turbine health monitoring, diagnostics, and prognostics: A survey. *IEEE Trans. Reliab.* **2018**, *67*, 1340–1363. [[CrossRef](#)]
5. Tahan, M.; Tsoutsanis, E.; Muhammad, M. Performance-based health monitoring, diagnostics and prognostics for condition-based maintenance of gas turbines: A review. *Appl. Energy* **2017**, *198*, 122–144. [[CrossRef](#)]
6. Urban, L.A. Gas path analysis applied to turbine engine condition monitoring. *J. Aircr.* **1973**, *10*, 400–406. [[CrossRef](#)]
7. Stamatidis, A.; Mathioudakis, K.; Berios, G. Jet Engine Fault Detection with Discrete Operating Points Gas Path Analysis. *J. Propuls. Power* **1991**, *7*, 1043–1048. [[CrossRef](#)]

8. Gulati, A.; Zedda, M.; Singh, R. Gas turbine engine and sensor multiple operating point analysis using optimization techniques. In Proceedings of the 36th AIAA/ASME/SAE/ASEE Joint Propulsion Conference and Exhibit, Las Vegas, NV, USA, 24–28 July 2000.
9. Sampath, S.; Ogaji, S.; Singh, R. Engine-fault diagnostics: An optimisation procedure. *Appl. Energy* **2002**, *73*, 47–70. [[CrossRef](#)]
10. Brotherton, T.; Volponi, A.; Luppold, R. eSTORM: Enhanced self tuning on-board real-time engine model. In Proceedings of the Intelligent Automation Corp Poway, Big Sky, MT, USA, 8–15 March 2003.
11. Lu, F.; Ju, H.; Huang, J. An improved extended Kalman filter with inequality constraints for gas turbine engine health monitoring. *Aerosp. Sci. Technol.* **2016**, *58*, 36–47. [[CrossRef](#)]
12. Yan, L.; Zhang, H.; Dong, X. Unscented Kalman-filter-based simultaneous diagnostic scheme for gas-turbine gas path and sensor faults. *Meas. Sci. Technol.* **2021**, *32*, 095905. [[CrossRef](#)]
13. Lin, L.; Liu, J.; Guo, H. Sample adaptive aero-engine gas-path performance prognostic model modeling method. *Knowl. Based Syst.* **2021**, *224*, 107072. [[CrossRef](#)]
14. Wang, C.; Zhu, Z.; Lu, N. A data-driven degradation prognostic strategy for aero-engine under various operational conditions. *Neurocomputing* **2021**, *462*, 195–207. [[CrossRef](#)]
15. Xue, B.; Xu, Z.; Huang, X. Data-driven prognostics method for turbofan engine degradation using hybrid deep neural network. *J. Mech. Sci. Technol.* **2021**, *35*, 5371–5387. [[CrossRef](#)]
16. Saxena, A.; Goebel, K.; Simon, D. Damage propagation modeling for aircraft engine run-to-failure simulation. In Proceedings of the 2008 International Conference on Prognostics and Health Management, Denver, CO, USA, 6–9 October 2008.
17. Dong, K.; Gao, Y.; Jing, L. Correlation tests of the engine performance parameter by using the detrended cross-correlation coefficient. *J. Korean Phys. Soc.* **2015**, *66*, 539–543. [[CrossRef](#)]
18. Zedda, M.; Singh, R. Gas turbine engine and sensor fault diagnosis using optimization techniques. *J. Propuls. Power* **2002**, *18*, 1019–1025. [[CrossRef](#)]
19. Diakunchak, I.S. Performance Deterioration in Industrial Gas Turbines. *J. Eng. Gas Turbines Power* **1992**, *114*, 161–168. [[CrossRef](#)]
20. Aker, G.F.; Saravanamuttoo, H.I.H. Predicting Gas Turbine Performance Degradation Due to Compressor Fouling Using Computer Simulation Techniques. *ASME J. Eng. Gas Turbines Power* **1989**, *111*, 343–350. [[CrossRef](#)]
21. Zhang, J.; Sanderson, A.C. JADE: Adaptive differential evolution with optional external archive. *IEEE Trans. Evol. Comput.* **2009**, *13*, 945–958. [[CrossRef](#)]
22. Storn, R.; Price, K. Differential Evolution—A Simple and Efficient Heuristic for global Optimization over Continuous Spaces. *J. Glob. Optim.* **1997**, *11*, 341–359. [[CrossRef](#)]
23. Das, S.; Suganthan, P.N. Differential evolution: A survey of the state-of-the-art. *IEEE Trans. Evol. Comput.* **2011**, *15*, 4–31. [[CrossRef](#)]
24. Biswas, P.P.; Suganthan, P.N.; Amaratunga, G.A.J. Minimizing harmonic distortion in power system with optimal design of hybrid active power filter using differential evolution. *Appl. Soft Comput.* **2017**, *61*, 486–496. [[CrossRef](#)]