Review Article

Aero-Engine Real-Time Models and Their Applications

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Aero-engine real-time models are widely used in control system design, integration, and testing. They can be used as the basis for model-based engine intelligent controls and health management, which is critical to improve engine safety, reliability, economy, and other performance indicators. This article provides an up-to-date review on aero-engine real-time modeling methods, model adaptation techniques, and applications for the last several decades. Besides, future research directions are also discussed, mainly focusing on the following four areas:(1) verification of the aero-engine real-time model over the full flight envelope; (2) better balance between real-time performance and accuracy in simplified methods for the aero-thermodynamic component level models; (3) further improvement in the real-time performance for the identified nonlinear models over the full flight envelope; (4) improvement of hybrid on-board adaptive real-time models combining the advantages of both model-based and data-based on-board adaptive real-time modeling methods.

1. Introduction

Due to the harsh working environment of the aircraft engine, the aero-thermodynamic process is complex, and its characteristics can only be described by a complex multivariate time-varying model with strong coupling and nonlinearity. Real-time aero-engine models with high accuracy have been rigorously pursued. Consequently, much research has been conducted, and many important results have been obtained. In SAE AIR4548 standard, a real-time engine model is defined as a transient performance computer program, whose engine outputs are generated at a rate commensurate with the response of the physical system it represents [1]. In essence, the real-time model of the engine is equivalent to a digital engine, and it can calculate the steady-state and transient characteristics of the engine within the entire flight envelope in real time with a certain accuracy, which reflects the actual working state of the current engine. This obviously forms important aspects of propulsion simulation and becomes the basis for advanced health management systems.

As early as the 1970s, in order to develop the aero-engine controllers in software and hardware platforms, researchers began to study real-time models. The early real-time models were primarily simple analog devices. In 1972, Seldner et al. [2] successfully performed real-time simulation of steady and dynamic performance of the J85-13 turbojet engine on an analog computer. With the increasing demand for real-time models, the analog model shows the disadvantages of low precision, high cost, and difficulty in use. The digital model with low cost begins to enter the view of modeling researchers. Koenig et al. [3, 4] developed digital model programs GENENG and GENENG II for calculating the design and nondesign point performance of turbojet and turbofan engines. This early digital model is simply a simple digitization of the analog model, whose real-time capability and precision are also limited. In the mid-1970s, when digital computer performance was limited, Szuch et al. [5, 6] used multiple analog-digital hybrid models, which run in collateral analog and digital processors to improve the performance of real-time simulation. They applied it to real-time simulations of TF30-P-3 and F100-PW-100 turbofan engines. Literature [7] summarized the modeling technologies of real-time models before the 1980s, and the author pointed out that the main difficulty of real-time modeling is the limited computing power of hardware. At that time, the

analog-digital hybrid model is the type of real-time model with the best comprehensive performance. Since then, with the rapid development of digital computer and Full Authority Digital Electronic Control (FADEC) technology, the digital model has gradually eliminated the analog model and the digital-analog hybrid model, becoming the mainstream of real-time models. According to different application requirements, various types of real-time models are put forward. In [8], real-time engine modeling technologies in the 1980s and 1990s are summarized, and the author points out that the on-board real-time modeling technology is the advanced research direction of real-time modeling. Besides, the author also predicts that the main development direction of the real-time model in the future is the self-adaption improvement combined with intelligent advanced algorithms. Since the beginning of the new century, with the rapid development of artificial intelligence technology, aero-engines have gradually entered the intelligence time, and the requirements of intelligent aero-engine propulsion systems for on-board adaptive real-time models are also increasing. As the basis of intelligent engine control, NASA, General Electric, Pratt & Whitney, and other institutions, companies, and research scholars have placed the research on high-precision on-board adaptive real-time engine models at the first priority. Review [9] offers a historical review of on-board modeling applied on gas turbine engines, and it also establishes its limitations, and consequently the challenges, which should be addressed to apply the on-board real time model to new and the next generation gas turbine aero-engines.

Up to now, in order to obtain real-time models with as high a comprehensive performance as possible after balancing real-time performance, adaptability, accuracy, and cost, a series of research achievements have been obtained. Based on the previous achievements, this paper gives a review of the development of aero-engine digital real-time modeling technology and its application field over the past decades. The structure of the article is as follows: the first chapter describes the real-time modeling method; the second chapter describes the modeling method of on-board adaptive real-time model based on the first chapter; the third chapter describes the application field of real-time model; the fourth chapter summarizes the above chapters and looks forward to the future development direction of real-time model.

2. Real-Time Modeling Method

The aero-engine modeling methods commonly used are divided into analytical methods and experimental methods [10]. The analytical methods use the characteristic data of each component and the constraints of the engine to establish a series of nonlinear equations describing the aero-thermodynamic characteristics of the engine. By solving the nonlinear equations, the steady and dynamic characteristics of the engine can be simulated in the full flight envelop. The nonlinear component-level model of the engine established by the analytical method has high precision, but the real-time performance is poor because of

the complex calculation process. It can only run offline at the ground state and needs to be simplified before the available real-time model can be obtained. Experimental methods are based on the principle of system identification. The whole engine is regarded as a "black box." Based on the engine input and output data set, a model equivalent to the measured system is determined from a given set of model classes. Experimental methods do not need the users to understand internal working mechanism and component characteristics of the engine. The real-time performance and accuracy of the model established by the experimental method depend on the selected model class and the identification principle.

2.1. Simplified Component-Level Real-Time Model. The simplified component-level real-time modeling method is basically the same as the component-level non-real-time modeling method. However, in order to ensure real-time performance without reducing too much accuracy, some minor aero-thermodynamic characteristics need to be neglected, and some approximate methods are adopted in the algorithm. These simplified methods are summarized as follows:

(i) Only retain low-frequency dynamics and ignore high-frequency dynamics: The most common high-frequency dynamics in aero-engines are volume dynamics. Ignoring the effect of volume dynamics is acceptable in most applications of real-time models, which does not reduce the precision too much.

(ii) Improve the interpolation algorithm for component characteristic curves: Characteristic curves of the compressor and turbine usually have a large amount of data. Interpolation calculations of component characteristics are required in each cycle, which has a great influence on the real-time performance of the model. A common simplification method is to optimize the interpolation algorithm [11, 12] or use a polynomial not higher than three times or other function to fit [13, 14], thus avoiding interpolation.

(iii) Simplify the formulas of aero-thermodynamic calculation: The aero-thermodynamic calculation process of the component-level model involves complex calculations such as power exponents and differential equations, as well as the possible time-consuming problem of internal variable specific heat iterated calculations. Simplifying the principle formulas can reduce the complexity of calculation, which in turn improves real-time performance. These methods include approximating the compressor's temperature ratio to a piecewise function of the pressure ratio to avoid a power exponent [15], establishing an interpolation table for thermal property parameters of gas [12] and so on.

(iv) Improve iterative algorithms, reduce the number of loop iterations, or even use modeling methods without iteration:The component-level model usually uses the Newton–Raphson method to iteratively

solve the equilibrium equations. Although this algorithm has high precision, it is usually inferior in real-time performance. Scholars have done a lot of researches on improving the real-time performance in this aspect. These methods include reducing the number of iterations by optimizing the selection of initial guess values [16], using improved iterative algorithms such as the Broyden method [12, 17, 18] or even bringing in the variables and equations in volume dynamics to avoid iterative calculations directly [19, 20].

The simplified methods and results of the component-level real-time model are shown in Table 1.

2.2. Identified Real-Time Model.

System identification is a data-driven modeling method. By giving the input signal, using the input and corresponding output data of the aero-engine test, the optimal fit between the data and the model is found through a certain identification algorithm. This identified modeling method does not require much understanding of the internal engine process.

In general, the identification method is divided into nonparametric model identification method and parametric model identification method [21]. When using nonparametric model identification method, it is not necessary to determine the specific structure of the model in advance, and the response curve of time or frequency is used to describe the system, such as impulse response, step response, and frequency response; When using parametric model identification method, the specific structure of the model needs to be chosen, and the model parameters are estimated by minimizing the error criterion function between the model and the system. Generally speaking, the transfer function model and the state-space model are the most basic parameter identification models. The nonparametric model obtained by the identification algorithm can be transformed into a parametric model after appropriate processing. The classification of identified real-time models is shown in Figure 1.

2.2.1. Linear Identified Real-Time Model.

Since linear system theory has developed very maturely, the development of accurate aero-engine linear model is of great help to engine control. If there is an accurate linear real-time model of the engine, it is possible to carry out a large number of control methods based on linear control theory and improve the design of aero-engine control system. Establishing the linear identified real-time model of engine is usually based on high-precision aero-thermodynamic component-level model or test data, which can be divided into two categories: time domain and frequency domain.

The most commonly used linear identified real-time model is linear parameter varying (LPV) model in time domain identification. The concept of LPV system was first put forward by Shamma in 1990s, and its structure is as follows:

$$x = A(\alpha)x + B(\alpha)u,$$
$$y = C(\alpha)x + D(\alpha)u, \tag{1}$$

in which $x \varepsilon R^n$ is the state vector; $y \varepsilon R^n$ is the output vector; $u \varepsilon R^p$ is the control vector; $\alpha \varepsilon R^j$ is the scheduling parameter vector.

The basis of the aero-engine LPV model is the component-level model. Generally speaking, the two most critical steps in establishing a LPV model are obtaining accurate small deviation state space models in steady-state points and choosing the appropriate scheduling method. Partial derivative method and fitting method are commonly used to obtain a small deviation state space model [22]. As early as 1978, Geyser [23] had already developed a tool DYGABCD to calculate A, B, C, and D matrices of the state-space model on each steady-state point using a nonlinear engine model. Up to now, traditional parameter scheduling methods include linear interpolation and fitting of a polynomial (no more than 3-order), and the scheduling parameter α is usually rotational speed, and they have huge room for improvement in accuracy and real-time performance. Domestic and foreign scholars mainly research and improve these two aspects.

In terms of improving the accuracy and real-time performance of the small deviation state space model, Mihaloew and Roth [24] and Daniele [25] consider that the traditional partial derivative method uses a positive perturbation for a given small disturbance amount, which will result in the problem that obtained state-space model may have a large dynamic error in the field below the steady state point. So the symmetric perturbation method is used to reduce this error. In addition, Daniele's research has established a reduced-order model for the problem of excessive output parameters in the F100 engine. It improves the real-time performance of the LPV model. Sugiyama [26] proposes a corresponding solution to three problems: (1) the indefinite selection criterion of the small disturbance size in the partial derivative method; (2) the indefinite calculation method of the partial derivative; (3) the excessive gap of the coefficient matrix in the whole flight envelope. Duyar et al. [27] calculate the coefficient matrix of state space model by α standard method. Kim et al. [28] apply the variable perturbation to the small perturbation method in obtaining the partial derivative needed in state space model, and the fuzzy logic is used to select the large, medium, and small sizes to solve the convergence problem of the solver in the nonlinear starting model at low speed during linearization. In addition, using artificial intelligence algorithms such as genetic algorithms [29], particle swarm optimization algorithms [30] and so on can also effectively improve the accuracy of the small deviation state space model.

In terms of improving scheduling methods, Kulikov et al. [31] use an interpolation scheduling parameter, which considers high and low speeds synthetically, and a real-time model of a twin-shaft turbojet engine has been established successfully by using this interpolation scheduling method. Yang et al. [32] comes up with a nonaffine parameter-dependent LPV modeling method, and the polynomial-based

TABLE 1: Simplification methods for component-level real-time models.

| Reference	Year	Simplified method	Verification scope	Real-time performance	Accuracy
[13]	1981	(1), (2)	62.5% to 100% state on the ground	Single-step running time on Xerox Sigma8 is 5.7 ms	No description
[15]	1991	(1), (3)	55% to 95% in sea level	Single-step running time on 80836 Microcomputer system is less than 10 ms	Within the allowable error of the project
[14]	1994	(1), (2)	Idle state to maximum state	Single-step running time on 33M IBM-PC/386 is 25 ms	Relative error≤5%
[17]	2001	(1), (4)	Idle state to maximum state	Single-step running time on 90 MHz Pentium II <15 ms	≤1%
[19]	2003	(4)	The whole flight envelope	No description	No description
[20]	2004	(4)	Ground state and two acceleration progresses in Ma = 0.3, H = 3 km state	Single-step running time on IBM/PC Pentium III 866 is 1 ms	≤1%
[18]	2010	(1), (4)	Idle state to maximum state	No description	No description
[11]	2017	(1), (2), (4)	Ma:0~0.8 H:0~15 km	No description	≤5%
[12]	2017	(1), (2), (3), (4)	70% to100% in sea level	Single-step running time on 168 MHz STM32F407 is 1.55 ms	≤0.2%
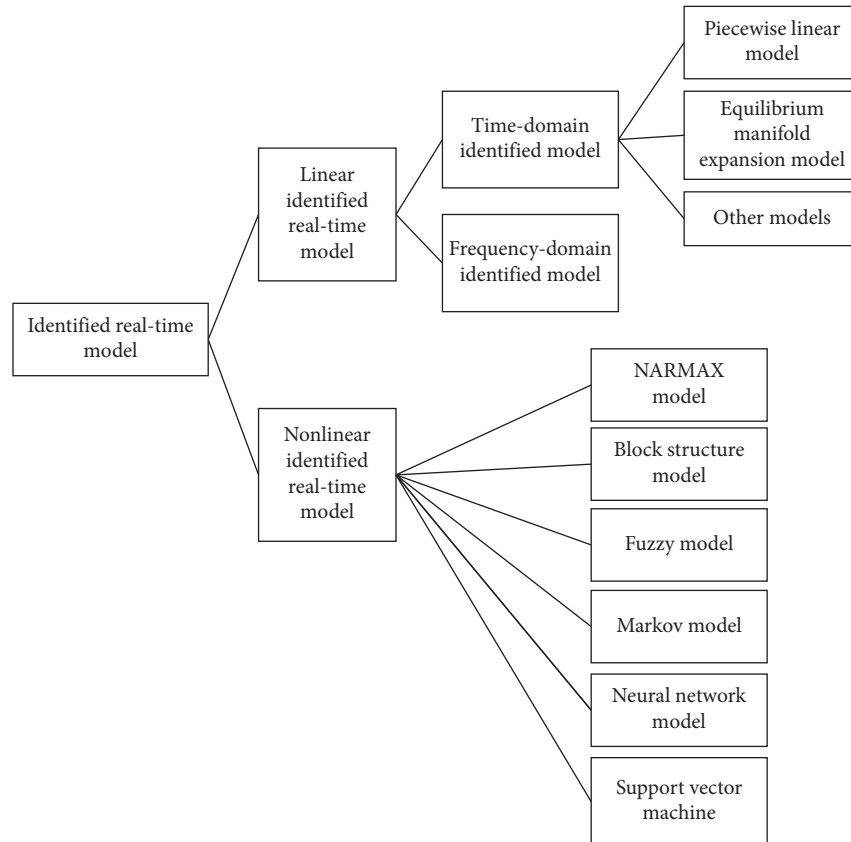
FIGURE 1: Classification for identified real-time models.

LPV modeling method is firstly employed to obtain the basis matrices, and then the Radial Basis Function Neural Network (RBFNN) is introduced for the online estimation of the nonaffine model parameters, which improves the simulation performance.

The LPV model is widely used, but it also has inherent problems. The accuracy is generally low in the dynamic process segments with large nonlinearity and large transient response. To solve these problems, colleges as well as research institutions constantly explore new modeling methods for linear identified real-time models in time domain.

In 2002, the Institute of Advanced Dynamics of Harbin Institute of Technology proposed a linear variable parameter model with nonlinear characteristics constructed by the linearized model—expansion model based on equilibrium

manifold [33]. Compared to the LPV model, the effective range is extended to all steady-state points. The algorithm of equilibrium manifold expansion model is simple and easy to implement. It does not require detailed component characteristic data during modeling. Besides, it can even quickly establish a simplified model of the engine at any time by using a two-step identification method of dynamic and static separation. According to the value of the scheduling variable, the quasistationary working equation of the engine and the related output parameter equation in the state of the current scheduling variable can be directly obtained. When establishing an equilibrium manifold expansion model, the selection of scheduling variables and the mapping type of working points are the main factors that determine the accuracy and real-time performance of modeling. After more than ten years of development, the equilibrium manifold model has great potential application value in hardware-in-loop and on-board models [34, 35].

In order to make the state variable model have the ability to update online, Pang et al. [36] directly uses the engine component-level model to obtain the exact partial derivatives online. Then, the accurate state variable model at any operating point can be calculated online, too. Compared to piecewise linearization model established offline, this method can get the state variable model online, which improves the accuracy of the real-time model.

In addition, real-time modeling methods proposed by other scholars in the time domain include dynamic equations method [37], novel generalized describing function (NGDF) method [38], analytical linearization method [39], dynamic coefficient method [40], multilevel identification method [41], and hybrid method [42] (transfer functions combined with fitted functions). From three most important criteria of aero-engine real-time model, accuracy, real-time performance, and application of range, all linear identified real-time modeling methods in time domain are summarized in Table 2.

In addition to the time domain identified modeling method, the frequency-domain identified modeling technique has great potential for establishing a model that can reflect physical features and precision requirements. The frequency-domain model can also be used to directly estimate the transfer function model. In frequency-domain identified modeling, it is especially important to select the appropriate excitation signal that can excite all modes of the system. In the early 1990s, the US Air Force began to apply the frequency-domain system identification method to aircraft control system design and developed a definite identification process [43]. After that, the researchers began to apply the frequency-domain identification method of the aircraft control system to the establishment of the real-time model of the aircraft engine. Evans et al. [44, 45] use multiple sinusoidal signals as excitation signals for frequency-domain identification to obtain the nonparametric model and parametric model of the engine. For models of different order, a series of engine operating points are selected, and the most excellent identification model is judged by calculating the cost function and the error autocorrelation function. This method is verified based on the test data of Rolls-Royce's dual-rotor Spey MK202 engine. Schoukens et al. [46] use a random sinusoidal signal to establish a linear dynamic model, which replaces the nonlinear dynamic model. This study defines the concept of Relevant Linear Dynamic System (RLDS) towards Nonlinear System (NLS) and establishes the relationship between RLDS and NLS by random numbers. The parameter model is set by using RLDS, and it proves that this model has good convergence to RLDS. Liu [47] designs a multisinusoidal excitation signal suitable for aero-engine identification and establishes a constrained frequency-domain maximum likelihood criterion function based on the compound normal probability distribution, and the least square method is used to establish the estimated value of parameters. In his results, a multivariable frequency-domain maximum likelihood identification method with constraint is proposed, which has better suppression of noise and improves the accuracy of the linear model of the engine.

2.2.2. Nonlinear Identified Real-Time Model. As the performance requirement of the aero-engine continues to increase, the accuracy requirement of the identified real-time model is also constantly increasing. The accuracy of the traditional linear identified model is hard to be further improved. In recent years, the research on nonlinear system identification methods based on finite observation data sets has become more and more mature. Artificial intelligence algorithms, which have the characteristics of association, fuzzy ability, and high nonlinear processing ability, have developed rapidly, and more and more applications begin to be applied to the field of aero-engine real-time modeling. These types of models include NARMAX model, block structure model, fuzzy model, Markov model, neural network identification model, and support vector machine (SVM). Such identification models usually rely on a large amount of data training, the computational complexity is usually high, and the real-time performance and accuracy are difficult to balance, so they have great potential to improve. This section briefly summarizes the above principles of nonlinear identification models and the corresponding real-time modeling research results.

(1) NARMAX model. The nonlinear auto regressive moving average (NARMAX) model is a universal nonlinear system structure proposed by Billings in 1982. It is suitable for describing nonlinear dynamic processes of aero-engine system, and it usually combines various artificial intelligence algorithms to identify parameters and optimize structure.

(2) Block structure model. Block structure models comprise Hammerstein model, Wiener model, Wiener-Hammerstein model, and Hammerstein-Wiener model. These models contain different cascade connections of nonlinear static systems and dynamic linear systems. Although these models are the simplest types of block-oriented nonlinear systems, they appear in many engineering applications.

TABLE 2: Summary of identified real-time linear modeling methods in time domain.

Reference	Year	Method	Analysis of research results
[24]	1982		Verification range is Ma: 0~0.2 and H: 0~5 km. Single step running time of the model on Xerox Sigma 9 is 8.9 ms and output error is less than 6%. This model method is fully verified in each aspect.
[25]	1979		Digital simulation verification range is the whole flight envelope (consist of 6 typical operating point, but it has no hardware verification and accuracy has no description.
[26]	1994		Digital simulation verification range is the whole flight envelope and model relative error is about 2%, but it has no hardware verification.
[27]	1992		Digital simulation verification range is 87% to 99% state on the ground and model relative error is about 4%, but it has no hardware verification.
[28]	2006	LPV method	Digital simulation verification range is from idle state to maximum state and starting progress. No hardware verification and no accuracy description.
[29]	2006		Digital simulation verification range is $H = 0$, Ma = 0 and $H = 10$ km, Ma = 1.3. No hardware verification and no accuracy description.
[30]	2014		Digital simulation verification range is Ma: 0~1.2 and H: 0~11 km. Model relative error is about 3.5%, but it has no hardware verification.
[31]	2004		Digital simulation verification range is from idle state to maximum state on the ground. Model relative error is about 4%, but it has no hardware verification.
[32]	2019		Digital simulation verification range is from idle state to maximum state on the ground, 13 equilibrium points are selected. RMSE of the matrices A and B is less than 0.6. Model has no hardware verification.
[34]	2010		The scheduling parameter is selected as the corrected high-pressure rotation speed. Verification range is from 83% to 93% state on the ground and single step running time on 2.66 GHz CPU is 0.17 ms. Model relative error is less than 4%.
[35]	2018	Equilibrium manifold expansion	A fitting idea of preconstructing polynomial dynamic coefficients is proposed to improve the interpolation accuracy of dynamic coefficients. Verification range is Ma: 1.1~1.6 and H: 9~14 km and single-step running time on STM32F407 is less than 0.5 ms. No accuracy description in detail.
[36]	2018	Exact partial derivative online obtained method	Accurate state variable model at any operating point in the whole flight envelope can be calculated online. Average single step running time is less than 1.68 ms and model relative error is less than 2%.
[37]	1992	Dynamic equations method	The coefficients of the model are easy to determine, no iterations, and the adaptability is easy to expand. Hardware verification range is the whole flight envelope and single-step running time on HH-AT is 18 ms, model relative error is less than 3%.
[38]	2004	NGDF method	Verification range is from idle state to maximum state and accuracy of large transient response is improved. The model running on Pentium III 1~2s is as same as the real engine operating 2~4s.
[39]	2011	Analytical linearization method	Verification range is the whole flight envelope and accuracy of large transient response is improved. The real-time performance is equivalent to the piecewise linearization model. Normalized uncertainty of output in large transients is less than 0.07 (piecewise linear model is 0.18).
[40]	2015	Dynamic coefficient method	Verification range is from idle state to maximum state, single step running time on 100 MHz TMS320F2808 is 0.2 ms and accuracy of transient process is less than 6%. The structure is flexible and simple, it has good real-time performance.
[41]	2017	Multilevel identification method	The degree of fit is around 90%, which has great potential for improvement. This method can be applied to closed-loop systems whose controller parameters are unknown.
[42]	2017	Hybrid method	Verification is from 77% to 100% HP shaft speed on the ground. This method combines transfer functions with fitted functions. Dynamic modeling error is less than 3%.

(3) Fuzzy model. The fuzzy model is a model established by using fuzzy mathematics to describe certain features and internal relations of objective things. Because the fuzzy logic system has the characteristic of uniformly approximating any nonlinear function defined on a dense set in arbitrary precision, so it has been widely used in the field of nonlinear system identification in recent years. For the aero-engine, it is a nonlinear system with high uncertainty and difficult in establishing mathematical model, so the fuzzy modeling method may have great advantages.

(4) Markov model. The Markov model is a statistical model. The discrete dynamic system can be expressed as an N-order Markov process. Some scholars conduct researches on aero-engine identification based on Markov model.

(5) Neural network model. Neural network is a research hotspot in the field of artificial intelligence since the 1980s. It abstracts the human brain neural network from the perspective of information processing, establishes a simple model, and forms different networks according to different connection methods. The neural network uses the input and output data of the system to learn to make the specified function error value reach the given requirement, and the mapping relationship between input and output is summarized. The neural network is widely used in the identification of nonlinear systems such as aero-engines.

(6) Support vector machine. Support vector machine is a pattern recognition method based on statistical learning theory proposed by Vapnik in 1995. It shows many unique advantages in solving small sample, nonlinear, and high dimensional pattern recognition problems. Support vector machine has fewer adjustment parameters than neural network, and the modeling complexity is greatly reduced. So, the application of support vector machine to the identification of aero-engine dynamic process has great potential.

From the three most important criteria of aero-engine real-time model, accuracy, real-time performance, and application of range, critical discussions of modeling methods for nonlinear identified real-time models are shown in Table 3.

2.3. Summary. This chapter introduces different methods for building real-time models. The advantages and disadvantages are summarized in Table 4.

3. On-Board Adaptive Real-Time Model

Due to the normal aging of gas turbine engines from erosion, corrosion, fouling, and tip clearance change over the life cycle, the real-time model may be seriously mismatched with the real engine, because the engine performance deviates from its nominal state. To solve the model mismatch problem, on-board adaptive real-time model is required.

The establishment of the engine on-board adaptive real-time model is divided into two steps: one is to establish a high-precision real-time model of the nominal engine; the other is to implement the adaptation part for degraded engine. Several methods for nominal engine modeling have been introduced in detail in the above chapters. This section describes how to implement the adaptation part for the degraded engine.

The main idea for on-board adaptive real-time modeling is that once the engine malfunctions or degrades, the engine will deviate from the rated operation state. Any off-design operation of the engine will cause excursion of its output parameters, so we can estimate the off-design operating characteristics of the engine by the offset of the output parameters. At present, the methods for establishing an on-board adaptive real-time model mainly include adaptive real-time modeling method based on Kalman filter, data-based adaptive real-time modeling method, and hybrid adaptive real-time modeling method.

3.1. Adaptive Real-Time Modeling Method Based on Kalman Filter. The principle of the adaptive real-time modeling method based on Kalman filter is that, according to the deviation between the actual measured parameters of the engine and the estimated parameters calculated by the real-time model, extended Kalman filter technique is used to correct the based value of the real-time model online. This method is a combination of modern control theory and traditional modeling technology. It is especially suitable for automatic correction of the model in dynamic process, which can more fully reflect the operating state of the engine.

The schematic diagram of this adaptive modeling idea is shown in Figure 2. It contains the Kalman filter and the on-board nominal engine model. The modules are described in detail as follows:

3.1.1. Kalman Filter. In order to estimate the component performance degradation using the deviation between the model output and the actual engine measurable output, it is necessary to consider the effect of engine performance degradation in the engine state variable model. So, the engine health parameters (such as flow or efficiency of major components) need to become the state variables, and the engine piecewise augmented state variable model in the flight envelope is established offline. Then, the corresponding Kalman filter is designed as the state estimator. In the actual working process of the on-board adaptive real-time model, based on the offset between the estimated parameters from the real-time model and the actual engine measurement parameters, the designed Kalman filter is used to estimate the degradation of the health parameters of the engine, which makes the on-board real-time model perform adaptive correction.

3.1.2. On-Board Nominal Engine Model. The on-board nominal model usually adopts the simplified component-level model (CLM), linear identified models as introduced in chapter. The adaptive correction of the model is performed in real time through the degradation of the component health parameters estimated by the Kalman filter, and then the corresponding engine performance parameters (thrust, surge margin, etc.) can be updated.

For a long time, researchers have made some effective improvements to the adaptive modeling method based on Kalman filter and try to apply them on the actual engine. In the early 1990s, NASA used a "steady-state linear model + nonlinear performance parameter calculation + Kalman filter" composite real-time model in performance optimization control, which has been successfully applied on the F15/F100 engine [64, 65]. In 2002, Pratt & Whitney developed an on-board real-time model STORM. It used the estimated parameters of the Kalman filter to correct the

Table 3: Summary of identified real-time nonlinear modeling methods.

Reference	Year	Type	Analysis of research results
[48, 49]	1998, 2001		A multiobjective genetic algorithm based on the NARMAX model is proposed, verification range is 55%~85% rotational speed on the ground. Model accuracy of large transient is low and real-time performance has no description.
[50]	2016	NARMAX model	Semiphysical simulation experiments are carried out for real-time verification, verification range is from idle state to maximum state on the ground, and model accuracy is more than 92%.
[51]	2004		Volterra series model (a type of NARMAX model) is used describe the dynamic working process of the engine between the idle state to maximum state on the ground. Real-time performance has no description.
[52]	2014	Block structure model	Hammerstein-Wiener model is used. Simulation shows that the application range of each H-W model is larger than those linear models.
[53]	2020		Wiener model is used as the nominal engine model. Simulation shows that compared with piecewise linear model and NGDF, Wiener model is the best candidate for nominal engines on-board modeling when unmeasured parameters are concerned.
[54]	2007		Verification range is cruise state, real-time performance is poor because identification needs 20s, only offline modeling is available. Relative error is less than 0.15%.
[55]	2013	Fuzzy T-S model	Compared with [54], verification range is extended to the whole flight envelope. Identification time is shorten to about 1s, it is potential for online correction combined with real-time data. Relative error is less than 0.18%.
[56]	2018		Some contributions are made for identifying a T-S fuzzy model for turbofan aero-engines with guaranteed stability, which facilitates the application of the fuzzy control. Accuracy index NMSE is less than $3.4 * 10^{-3}$.
[31]	2004	Markov model	Verification range is from minimum thrust state to the take-off state on the ground, real-time performance is 20 times better than using the RBF neural network model. Average speed error is around 4 rpm.
[57]	2002		High accuracy in low frequency band simulation.
[58]	1998		No iteration is needed and suitable for online identification. Relative error is less than 10^{-4}.
[59]	2015	Neural network model	Offline training and real-time performance is poor. Accuracy index MSE is less than $3.28 * 10^{-5}$.
[60]	2000		Offline training and real-time performance is poor. Accuracy index MSE is less than $5.7 * 10^{-3}$.
[61]	2000		The training time is greatly reduced compared to the BP-based algorithm, and the number of training steps is only 20. Model relative error is less than 1.2% in large transient, but verification range is only in cruise.
[62]	2004	Support vector machine	Verification range is cruising and landing conditions. Relative error is less than 4%. Real-time performance has no description.
[63]	2010		Compare with [62], support vector machine learning speed is improved and sample size is reduced. Relative error is less than 0.35%.

Table 4: Comparison among different types of real-time models.

Type	Advantage	Disadvantage
Simplified component-level real-time model	Engine physical characteristics can be retained.	Difficult to balance the real-time performance and accuracy, little simplification can lead to huge accuracy loss.
Linear identified real-time model	Real-time performance is good, linear control theory can be applied.	Difficult to cover the whole flight envelope; low accuracy in large transient; robust problems may arise when piecewise controllers are integrated.
Nonlinear identified real-time model	High approximation accuracy for nonlinear dynamic processes.	Difficult to meet the requirements of precision, data storage and real-time performance at the same time.

nonlinear on-board real-time model. One disadvantage of STORM is that it has limited scope for abrupt fault on some components. STORM has been successfully verified on the F22/F119 engine [66]. Suglyama [67] designs a constant gain extended Kalman filter to improve the real-time performance of the traditional extended Kalman filter gain calculation. This method has completed the feasibility verification on the single-axis turbojet engine. Chen [68] proposes an improved Kalman filter with input integral compensation for the problem that the traditional Kalman filter designed at a design point has small applicable range, which solves the problem of estimation accuracy and application range. In addition, the standard orthogonal decomposition method is used to design an adaptive model of
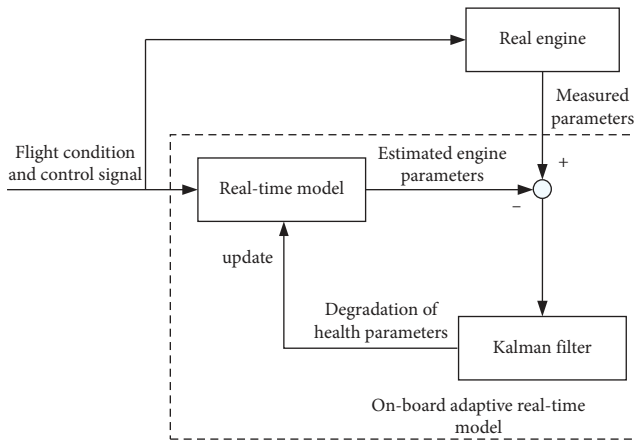
FIGURE 2: Block diagram of adaptive real-time model based on Kalman filter.

FIGURE 3: Block diagram of adaptive real-time model based on data.

the reduced-order Kalman filter based on the engine with only a few sensors operating smoothly. Compared with the traditional method, the accuracy of this method is not reduced, and it is more practical, and this method is needed to be verified in a real engine in the future work.

Through these researches results, we can find that practicality can be improved by (1) simplifying the Kalman filter design method such as reducing numbers of Kalman filters; (2) adopting a constant gain. The main problem for adaptive real-time modeling methods based on Kalman filter is how to extend the applicable range of the Kalman filter at one design point.

3.2. Data-Based Adaptive Real-Time Modeling Method. Since the beginning of the 21st century, with the development of artificial intelligence technology, data-based adaptive modeling methods have begun to receive attention in the field of adaptive real-time models, such as neural networks and support vector machines. Compared to Kalman filters, the adaptive module based on data does not need to know the characteristics of the physical object; it only needs to transform the input and output data of the research object. The data-based adaptive real-time modeling method selects some suitable engine measurable parameter offsets as inputs, and it takes the component performance degradations, which reflect the engine health condition as outputs. Block diagram of adaptive real-time model based on data is shown in Figure 3.

The literatures [69, 70], respectively, use BP and MGN neural network to replace the Kalman filter to establish the corresponding adaptive module in the on-board real-time model. Wei et al. [53] propose an on-board modeling structure named Hybrid Wiener model (HWM). In this research, Wiener model is chosen as the on-board nominal engine model, and the adaptation element updates the health parameters and steady-state operating lines based on postflight data after each flight cycle to match the specified engine with the most possible effort. What these studies have in common is that the adaptation approaches are all offline.
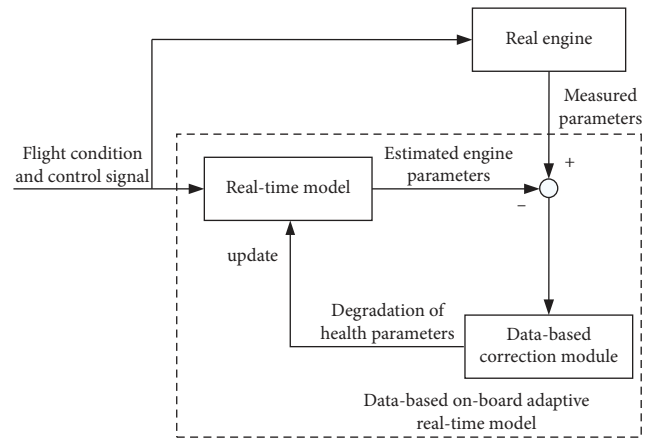
3.3. Hybrid Adaptive Real-Time Modeling Method. In order to combine the advantages of model-based and data-based adaptive modeling methods, a hybrid adaptive real-time modeling method comes out. The principle of this method is that, on the basis of original adaptive model based on Kalman filter, the data-based correction module is added to correct the modeling error of the on-board nominal model, which can improve the estimation accuracy of Kalman filter on the degradation of real engine component parameters. To realize the modeling of this hybrid adaptive real-time model, it is necessary to use a large number of engine test data to perform offline training on the data-based correction module. The inputs are flight condition and control signals, and the outputs are the modeling errors between the on-board real-time model and the actual engine. The hybrid adaptive real-time model block diagram is shown in Figure 4.

In the past decade, research institutions and scholars have also carried out a series of study on hybrid adaptive real-time models. On the basis of STORM, Pratt & Whitney combined the neural network correction module to establish an enhanced hybrid on-board real-time model eSTORM [71–73], which improves the reliability of Kalman filter. eSTORM has been successfully verified on the PW6000 engine. Based on the traditional model-based adaptive real-time modeling method, Lu and Huang [74] propose the application of adaptive genetic algorithm to the parameter selection of least squares support vector regression machine and establish the NARMAX model correction module. The output of the model correction module is used to compensate the output of the on-board adaptive model online, which effectively reduces the error between the real engine and the on-board adaptive real-time model. Practicality of this research also needs to be verified in the real engine.

3.4. Summary. This chapter introduces three main types of methods for establishing an on-board adaptive real-time model. The advantages and disadvantages are summarized in Table 5.

In addition, as the performance requirements of the new generation of fighters are getting higher and higher, the
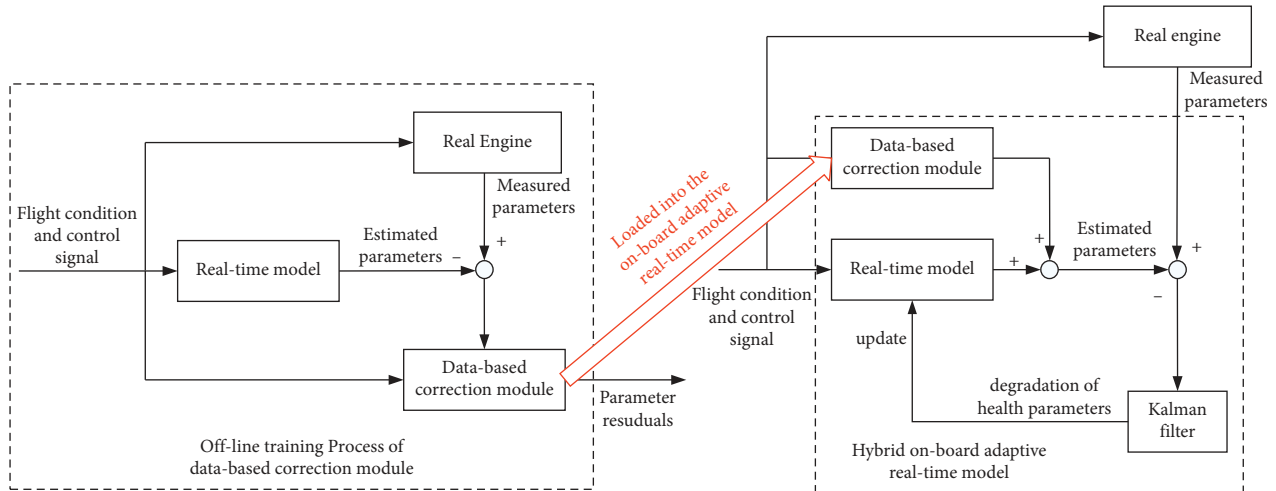
FIGURE 4: Block diagram of hybrid adaptive real-time model.

TABLE 5: Comparison among different types of on-board adaptive real-time model methods.

Method	Advantage	Disadvantage
Kalman filter based on-board adaptive real-time model	Design process and theoretical support are mature.	Applicable range of each KF is very limited. There will be a large amount of stored data when applied in the full flight envelope.
Data based on-board adaptive real-time model	Physical characteristics of the engine are not needed.	Theoretical proof of how to achieve engine adaptation is lack. Large amount of flight data is needed.
Hybrid on-board adaptive real-time model	Structural flexibility is large. Advantages of other methods can be combined.	Structure is complex and a large amount of flight data is needed. Real-time performance has great potential for improvement.

function of the on-board adaptive real-time model will become more complex. The study of integrated on-board real-time model equipped with the tip clearance model, the icing model, the variable geometry model, and the intake model may become an advanced research field for future real-time models.

4. The Applications of Real-Time Model

The real-time model of the aero-engine is widely used. It is not only the basis for the hardware-in-the-loop and semi-physical real-time simulation, test, and verification of the control system, but also the basis for the aircraft iron bird test and flight simulator. Besides, it is the necessary part for on-board model-based engine control, fault diagnosis, and health management.

4.1. Real-Time Simulation Test on the Ground. The real-time simulation test on the ground includes the hardware-in-the-loop simulation (HIL), semiphysical simulation, and the aircraft iron bird test. The real-time model of the aero-engine is an indispensable part, whose performance directly affects whether the entire ground test will success.

At present, in the development of FADEC system, the cycle iterative design approach of "all-digital simulation"- "hardware-in-the-loop simulation (HIL)"-"semiphysical simulation"-"engine platform test"-"flight verification" is adopted, which can shorten the development cycle and

reduce the design cost. Since the all-digital simulation is only a preliminary test of the control algorithm, the engine model used in the simulation is generally not real-time in pursuit of accuracy, so the real-time performance of the controller cannot be verified. The reliability of the simulation result is not enough for practical applications. In addition, it is difficult to implement the platform test and flight test verification, because the cost is too high. Finally, the hardware-in-the-loop simulation and semiphysical simulation test with the characteristics of low difficulty, relatively low cost, and closeness to the actual operating environment of the engine become the most important part of the design and development of the whole engine control system [75]. Hardware-in-the-loop simulation introduces the physical controller, driving and signal conditioning module, interface simulator, and other physical objects into the loop to complete the preliminary comprehensive verification of the control system. The schematic diagram is shown in Figure 5. The real-time models of the engine, sensors (LVDT is taken as an example), and actuators (the fuel supply model and the oil needle model are taken as examples) are included in the model computer. The entire hardware-in-the-loop simulation needs to be real-time. The schematic diagram of the semiphysical simulation is shown in Figure 6. Based on the hardware-in-the-loop simulation, the real power system and fuel system are brought into the circuit, which makes the verification platform closer to the actual operating environment of the engine. In the entire semiphysical simulation platform, except for the real-time
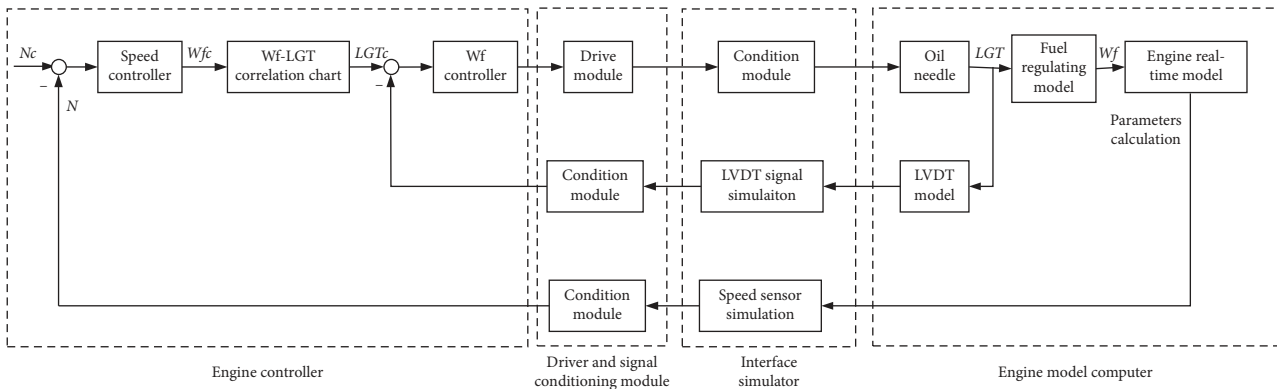
FIGURE 5: Experimental schematic diagram of aero-engine hardware-in-the-loop simulation.
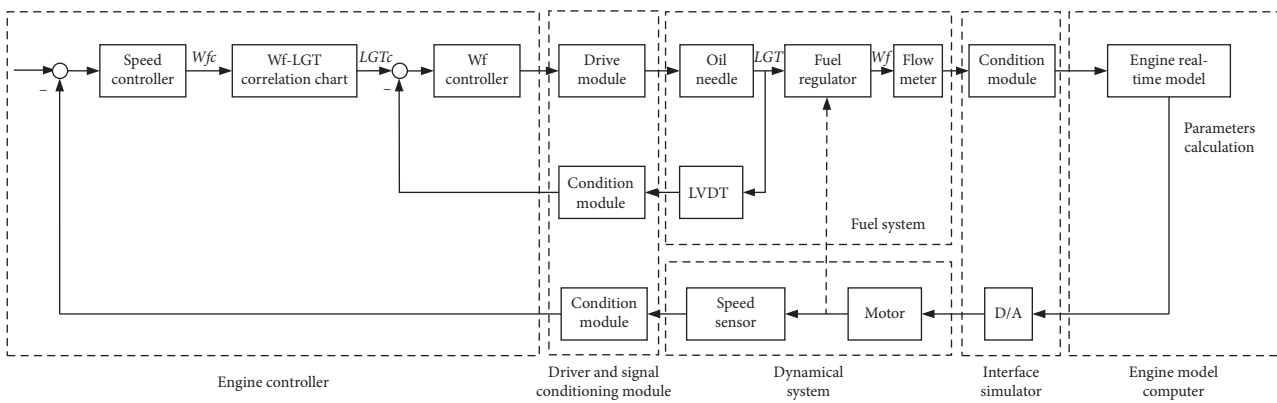

FIGURE 6: Experimental schematic diagram of aero-engine semiphysical simulation.

model of the engine, the components of the control system are almost all real parts [76].

Whether it is hardware-in-the-loop or semiphysical simulation test, as the feedback source of the engine controller and the controlled object, the engine real-time model is undoubtedly the core of the whole system, and its performance directly affects the reliability of the whole test. It is necessary to ensure that the model computer loaded with the engine real-time model has high computational performance. On the other hand, the most important point is to design a real-time engine model that can balance real-time performance and accuracy.

The aircraft iron bird test bench is called "flying control hydraulic system comprehensive test bench," which is a key test facility essential for aircraft system integration, optimization design, airworthiness forensics, delivery operation, and continuous airworthiness. The iron bird test bench is generally composed of a test bench, a hydraulic system, a flight control system, a landing gear system, a remote data interactive terminal, a console system, and a real-time flight simulation system including an engine real-time model. The structure diagram is shown in Figure 7. On the iron bird test bench, it is possible to verify that the function and performance of the aircraft's hydraulic system and its interaction with other systems on the aircraft are normal or not. The mechanical installation interface of the landing gear system, the

installation position of the accessories, the layout of the hydraulic piping, and the installation method of the flight control system in the "Iron Bird" are all consistent with the real aircraft. The real aero-engine is used by the high-precision real-time model instead. The entire iron bird system undertakes aircraft system-level R&D and verification, aircraft multisystem comprehensive verification, and airworthiness verification of flight control systems, hydraulic systems, and landing gear systems, which provide important assurance for aircraft system integration, flight test safety, flight test troubleshooting, and subsequent aircraft improvements [77].

4.2. Flight Simulator. The flight simulator is a flight real-time simulation system that can simulate the aircraft's air flight state and flight environment on the ground. The flight simulator is mainly composed of a console system, a data interaction terminal, a real-time flight simulation system including an engine real-time model, an audio, instrument, and a vision system. The structure diagram is shown in Figure 8. The real-time flight simulation system contains real-time models describing aircraft, engine, and on-board systems. It is the main component of the entire flight simulator and the basis for the normal operation of the flight simulator. Current flight simulator applications fall into three general categories, which include engineering
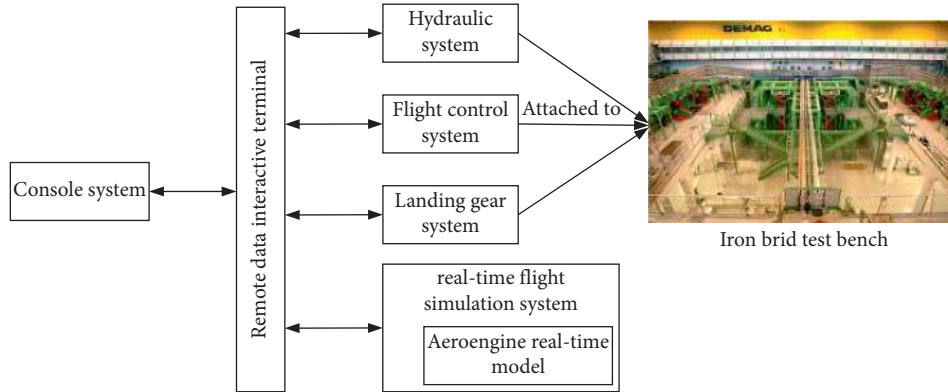
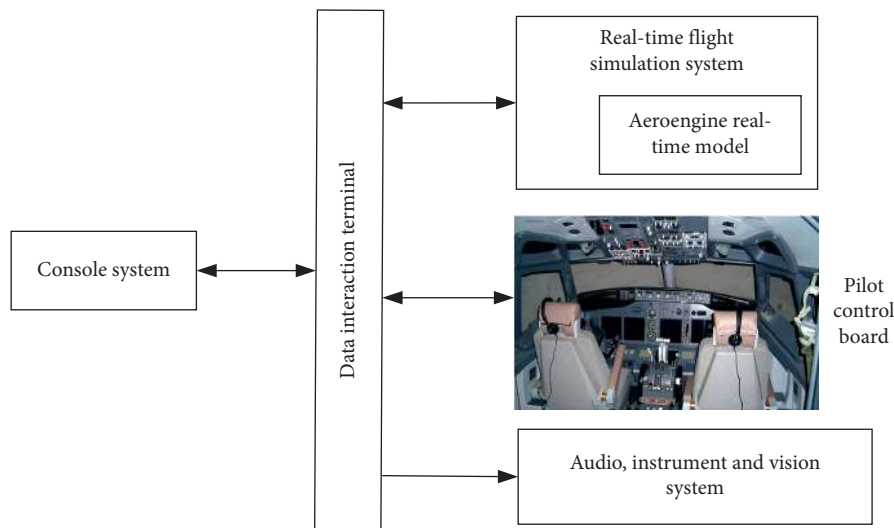FIGURE 7: Diagram of aircraft iron bird testing facility.

FIGURE 8: Diagram of flight simulator.

development, crew training, and maintenance training simulation devices [1].

4.2.1. Engineering Development Simulators. These simulators are usually used for "man in the loop" studies; they can evaluate the flight performance of the whole aircraft and the performance of the operating system, flight display system, instrument display system, and other systems. By continuously modifying the parameters of each system, they are repeatedly tested to obtain the optimal performance of the system.

4.2.2. Crew Training Simulators. These simulators are used to train crew members in the proper use and control of aircraft systems, including normal and emergency procedures. Further, these devices are also used for instruction in the theory and operation of specific aircraft systems and their components. In these devices, a multitude of system failures can be caused, which can result in realistic cockpit indications and cues. Using these crew training simulators can not only be free from meteorological conditions and site constraints, but also save energy and protect environment.

4.2.3. Maintenance Training Simulators. These simulators are a relatively recent simulator application. As the functions of the new generation aircraft cockpit become more and more complex, it is also very important to train the maintenance staffs responsible for the on-board systems. With these simulators, the maintenance staff can perform fault simulation tests on various on-board equipment in the cockpit and receive the corresponding results. They can use these data for analysis to train their equipment maintenance capabilities in the event of a real cockpit failure. Maintenance staff can find the problem of on-board equipment faster and more accurately.

4.3. Model-Based Control, Fault Diagnosis, and Health Management. Advanced aero-engine FADEC systems are not only limited to protection limit control and thrust control, but may also include direct turbine front temperature control, direct surge margin control, and performance optimization control. In addition, the FADEC system requires real-time fault diagnosis, tolerance, and health management for the aero-engine, including sensor redundancy reconstruction, engine performance degradation

estimation, and component life analysis. These new FADEC system functions all require the real-time engine model. Overall, the FADEC system can be divided into three layers in terms of ensuring the safety and reliability of the engine: the hardware layer, the basic control layer, and the performance management layer [78]. The structure diagram is shown in Figure 9. It can be seen that the aero-engine real-time model is the most important part in the entire control and performance management level. Aero-engine control, fault diagnosis, and health management based on the real-time model are the mainstream working modes of the current advanced FADEC system.

Model-based control is a control law design method using the real-time model as part of the control loop. The block diagram of its basic control structure is shown in Figure 10. Aero-engines have some state variables critical to the safety and performance of aerospace engines, such as high-pressure turbine blade temperature, compressor surge margin, and net thrust. But most of these variables are unmeasurable or need complex and unreliable measurement systems. In the traditional sensor-based control law design method, measurable parameters such as rotational speed and pressure ratio are usually used to indirectly reflect unmeasurable performance parameters such as thrust and surge margin. In order to ensure that these unmeasured performance parameters are not exceeding the limitation, larger safety margin will remain, which in turn leads to not so good engine performance. When in actual flight, the FADEC of the aero-engine is embedded with a high-precision on-board adaptive real-time model as a virtual engine, running in parallel with the real aero-engine, and then it is possible to use the real-time model to calculate the unmeasurable variables of the aero-engine required for the current flight state. Combined with the measurable signals, we can implement the advanced multivariable control methods and ensure the performance keep best under the condition that the engine meets various safety restrictions [79, 80].

Taking model-based surge margin control as an example [81], the structure of the controller is shown in Figure 11. In the traditional min-max control structure, various types of limiters calculate the corresponding fuel flow through real engine measurement data and then give the actuator an optimal fuel control command through min-max selection logic, which causes the high-pressure compressor surge margin to be low during the acceleration process. In model-based surge margin control, surge margin control loop is added to the controller structure due to the virtual measurement data obtained by the real-time model, which directly limits the surge margin and greatly improves the engine dynamic performance during acceleration process.

These years, model-based control methods have been applied to more and more fields, such as NOx emissions monitoring [82] and engine start-up optimization [83]. It can be ensured that real-time model will play a more and more important role in advanced FADEC system in the future.

In addition, the on-board adaptive real-time model is also a core part of aero-engine fault diagnosis and health management. Real-time diagnosis of the engine in flight is critical to the improvement of aviation safety. The purpose of the fault diagnosis system is to detect faults as quickly as possible from the real-time output data obtained from engine operation and then avoid false positives. However, as the engine continues working, its component health parameters (efficiency and flow) will gradually decrease with the engine's operating cycle, which will result in degradation and excursions in output variables. The normal degradation of the engine is not a fault, but it often causes the false report of the fault diagnosis system [84]. In order to solve this problem, a health management system is needed to distinguish the engine information, fuse data, monitor the engine health, and predict the engine life and performance degradation [85]. A common method is to use the Kalman filter to establish an on-board adaptive real-time model coupled with the estimated performance tracking parameters, which has been described in detail in the adaptive real-time model in Chapter 2. Based on the offset of the measurable parameters of the engine, the engine performance deviation parameters are estimated by the Kalman filter, and then the estimated deviation parameters value can be used to calculate the correction of the engine unmeasurable parameters. By using the output estimation parameters of the on-board adaptive real-time model, the sensor's soft and hard fault diagnosis and fault-tolerant control can be carried out [86, 87]. In recent years, advanced intelligence algorithms have also been applied to improve the performance of model-based health management system [88, 89].

In summary, for aero-engines with changing conditions in the actual flight, whether it is for effective and accurate control, or to ensure accurate fault diagnosis and efficient health management, a high-precision on-board real-time model is indispensable.

5. Summary and Outlook

The development of aero-engine real-time models has been around 50 years, and it always focuses on how to make a balance between model accuracy and real-time performance. In the early days, because of the limited computer hardware capabilities, digital real-time models were mostly based on reduced-order linear models or component level models, which are simplified a lot, so their accuracies were low. With the rapid development of the computer and artificial intelligence technology in the past decade, the real-time performance of the engine real-time model has become relatively easy to achieve. More and more researches have been devoted to how to improve the adaptability of the on-board model and how to use the real-time model to estimate engine performance parameters more accurately. In these fields, a large number of advanced intelligent algorithms are applied to the on-board adaptive real-time model to perform the error correction of the real-time model, as well as the estimation of engine performance parameters. In the past few years, NASA Aeronautical Research Mission Directorate has introduced and updated a "New Blueprint for Transforming the Global Aviation," in which there are six major strategic advancements, and real-time system-level security assurance is one of
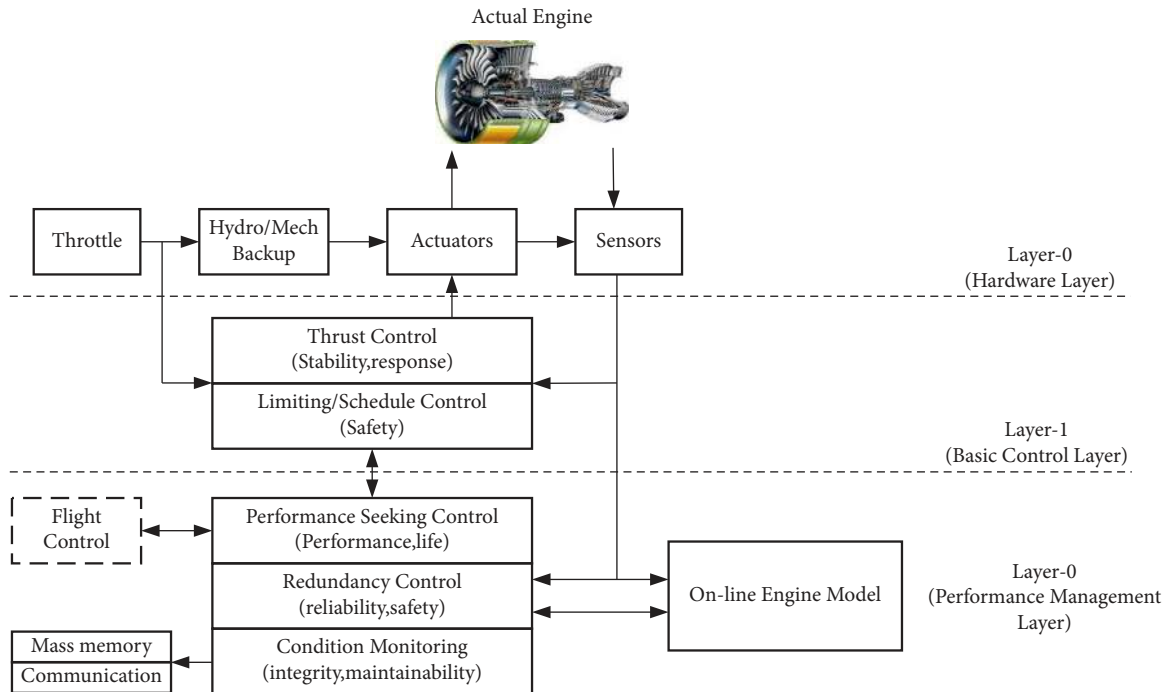
Actual Engine

Figure 9: Structure diagram for advanced aero-engine FADEC system.
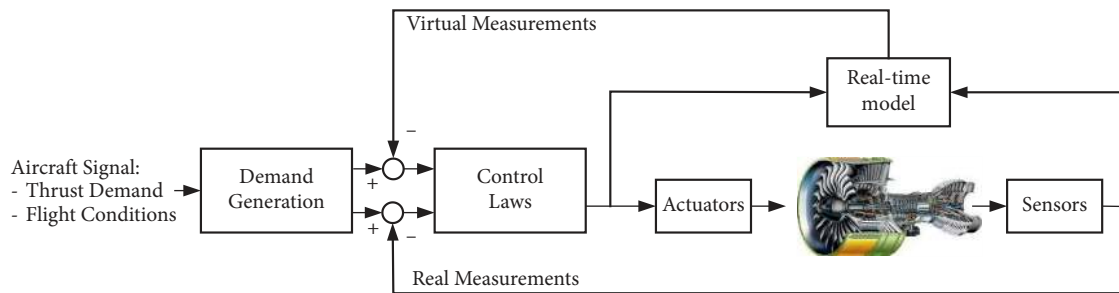

Figure 10: Real-time model-based control structure diagram.
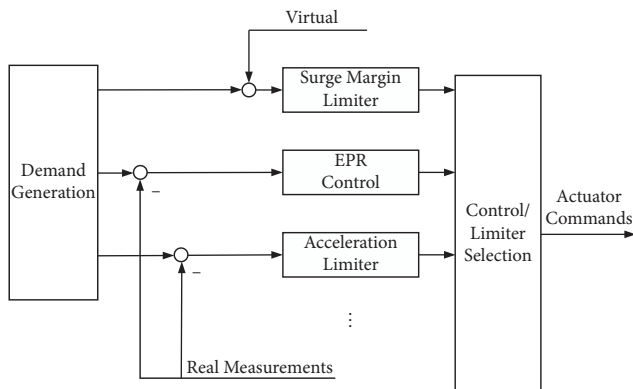

Figure 11: Structure diagram of surge margin model-based controller.

them [90]. This raises higher functional requirements for on-board adaptive real-time models in the future.

Looking forward to the future, the development trend of the aero-engine real-time model is as follows:

(1) Most researches relative to the real-time model only verify the performance in the envelope from the idle to the maximum state, and few researches are carried out on the establishment of aero-engine starting real-time model. So, it is imperative to research on how to establish a real-time model of the aero-engine that can be verified in the whole flight envelope.

(2) The nonlinear identification real-time model generally has poor real-time performance, and there are few researches applying this type of real-time model to the verification on the real hardware platform. Besides, the nonlinear identification real-time model relies too much on real engine test data, and it is difficult to theoretically prove the convergence of the model. Solutions to these problems must be studied in the future.

(3) Under the premise of high precision guarantee, the study on simplified methods of the aero-thermo-dynamic component level model will be the hot research direction. At the same time, as the

performance requirements of the engine become higher and higher, the real-time model will also be more complex. The integrated real-time model, which consists of the tip clearance model, the icing model, the inlet model, and so on, will become an important research field in the future.

(4) The on-board adaptive real-time model in the future will focus on the research of hybrid real-time model. It uses traditional Kalman filter to estimate the degradation of engine, and it also uses artificial intelligence algorithms to build a data-based model correction module to achieve correction of the on-board real-time model output parameters. Compared with a single model-based and data-based on-board adaptive real-time model, this hybrid adaptive real-time model combines the advantages and disadvantages of both, which is expected to improve the performance of the engine FADEC system and has great improvement and optimization potential.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

References

[1] SAE International, "Real-time modeling methods for gas turbine engine performance," Report No AIR4548, SAE International, Warrendale, PA, USA, 2013.

[2] K. Seldner, J. R. Mihaloew, and R. J. Blaha, "Generalized simulation technique for turbojet engine system analysis," Report No NASA-TN-D-6610, Lewis Research Center, Cleveland, OH, USA, 1972.

[3] L. H. Fishbach and R. W. Koenig, "GENENG-A program for calculating design and off-design performance for turbojet and turbofan engines," Report No.: NASA-TN-D-6552, Lewis Research Center, Cleveland, OH, USA, 1972.

[4] R. W. Koenig and L. H. Fishbach, "GENENG II-A program for calculating design and off-design performance of two- and three-spool turbofans with as many as three nozzles," Report No NASA-TN-D-6553, Lewis Research Center, Cleveland, OH, USA, 1972.

[5] J. R. Szuch and W. M. Bruton, "Real-time simulation of the TF30-P-3 turbofan engine using a hybrid computer," Report No. NASA-TM-X-3106, Lewis Research Center, Cleveland, OH, USA, 1974.

[6] J. R. Szuch and K. Seldner, "Real-time simulation of F100-PW-100 Turbofan engine using the hybrid computer," Report No NASA-TM-X-3261, Lewis Research Center, Cleveland, OH, USA, 1975.

[7] J. R. Szuch, "Advancements in real-time engine simulation technology," in Proceedings of the 18th Joint Propulsion Conference, Boston, MA, USA, July 1982.

[8] W. H. Yang and J. G. Sun, "New development of engine real-time modeling technology," Journal of Aerospace Power, vol. 10, no. 4, pp. 402–406, 1995, in Chinese.

[9] Z. Wei, S. Zhang, S. Jafari, and T. Nikolaidis, "Gas turbine aero-engines real time on-board modelling: a review, research challenges, and exploring the future," Progress in Aerospace Sciences, vol. 121, Article ID 100693, 2020.

[10] S. Q. Fan, Aircraft Engine Control Xian, Northwestern Polytechnical University Press, X'ian, China, 2008, in Chinese.

[11] H. Gazzetta Junior, C. Bringhenti, J. R. Barbosa, and J. T. Tomita, "Real-time gas turbine model for performance simulations," Journal of Aerospace Technology and Management, vol. 9, no. 3, pp. 346–356, 2017.

[12] K. Yin, W. X. Zhou, K. Qiao, and H. J. Wang, "Research on methods of improving real-time performance for aero-engine component-level model," Journal of Propulsion Technology, vol. 38, no. 1, pp. 199–206, 2017, in Chinese.

[13] J. R. Mihaloew, "A nonlinear propulsion system simulation technique for piloted simulators," in Proceedings of the 12th Annual Pittsburgh Conference on Modelling and Simulation, pp. 12–26, Pittsburgh, PA, USA, August 1981.

[14] Y. Liu, W. Liu, F. Q. Chen, and B. Sun, "A real-time simulation model of a twin-spool turbojet engine," Journal of Aerospace Power, vol. 9, no. 4, pp. 357–360, 1994, in Chinese.

[15] S. M. Liu and X. Y. Wang, "Digital real-time simulation of a twin-spool turbojet," Journal of Aerospace Power, vol. 6, no. 3, pp. 254–258, 1991, in Chinese.

[16] Y. F. Sui, "Real-time switching model of aeroengine," Aerospace Engineering, vol. 35, no. 2, pp. 13–16, 2009, in Chinese.

[17] A. Stamatis, K. Mathioudakis, J. Ruiz, and B. Curnock, "Real time engine model implementation for adaptive control and performance monitoring of large civil turbofans," ASME Turbo Expo, vol. 1, pp. 2–9, 2001.

[18] J. Lu, Y. Q. Guo, and S. G. Zhang, "Research on the iteration methods in aero-engine non-linear model real-time computation," Journal of Aerospace Power, vol. 25, no. 3, pp. 681–686, 2010, in Chinese.

[19] G. Yang, J. G. Sun, X. H. Huang, and W. S. Su, "A non-iterative method of aero-engine modeling using complementary variables," Journal of Aerospace Power, vol. 18, no. 2, pp. 198–202, 2003, in Chinese.

[20] K. M. Huang, J. Q. Huang, J. Liu, and J. B. Zhou, "An aeroengine real time model based on non-iterative method," Aerospace Engineering, vol. 30, no. 2, pp. 35–38, 2004, in Chinese.

[21] D. Y. Xiao, System Identification Theory and Application, Tsinghua University Press, Beijing, China, 2014, in Chinese.

[22] Z. P. Feng and J. G. Sun, "Modeling of small perturbation state variable model for aeroengines," Journal of Propulsion Technology, vol. 22, no. 1, pp. 54–57, 2001, in Chinese.

[23] L. C. Geyser, "A program for calculating linear ABCD Matrices from a nonlinear dynamic engine simulation," Report

No NASA-TP-1295, Lewis Research Center, Cleveland, OH, USA, 1978.

[24] J. R. Mihaloew and S. P. Roth, "A piecewise linear state variable technique for real time propulsion system simulation," Report No NASA-TM-82851, Lewis Research Center, Cleveland, OH, USA, 1982.

[25] C. J. Daniele, "Generation of linear dynamic models from a digital nonlinear simulation," Report No.: NASA-TP-1388, Lewis Research Center, Cleveland, OH, USA, 1979.

[26] N. Sugiyama, "Derivation of system matrices from nonlinear dynamic simulation of jet engines," *Journal of Guidance, Control, and Dynamics*, vol. 17, no. 6, pp. 1320–1326, 1994.

[27] A. Duyar, Z. Gu, and J. S. Litt, "A simplified dynamic model of the T700 turboshaft engine," *Journal of the American Helicopter Society*, vol. 40, no. 4, pp. 62–87, 1992.

[28] S. Kim, S. Ellis, and M. Challener, "Real-time engine modelling of a three shafts turbofan engine: from sub-idle to max power rate," *ASME Turbo Expo*, vol. 2, pp. 699–705, 2006.

[29] Q. H. Li and J. G. Sun, "Aero-engine state variable modeling based on the genetic algorithm," *Journal of Aerospace Power*, vol. 21, no. 2, pp. 427–431, 2006, in Chinese.

[30] B. Wang, X. Wang, Y. L. Shi, and H. W. Wang, "A real-time piecewise linear dynamic model of aeroengine," *Journal of Aerospace Power*, vol. 29, no. 3, pp. 696–701, 2014, in Chinese.

[31] G. G. Kulikov, H. A. Ceng, and Ph. D. Thompson, *Dynamic Modelling of Gas Turbines*, Springer London, London, UK, 2004.

[32] B. Yang, X. Wang, and P. Sun, "Non-affine parameter dependent LPV model and LMI based adaptive control for turbofan engines," *Chinese Journal of Aeronautics*, vol. 32, no. 3, pp. 585–594, 2019.

[33] Z. Q. Xu, "A wide range linearization method for thermal control in thermal power plants," Dissertation, Harbin Institute of Technology, Harbin, China, 2002.

[34] W. H. Hu, "Real-time simulation model for a turbofan engine based on nonlinear system equilibrium manifold theroy," *Journal of Aerospace Power*, vol. 25, no. 1, pp. 213–217, 2010, in Chinese.

[35] Y. J. Li, "Research on intelligent aero-engine performance seeking control technology," Dissertation, Nanjing University of Aeronautics and Astronautics, Nanjing, China, 2018.

[36] S. Pang, Q. Li, and H. Zhang, "An exact derivative based aero-engine modeling method," *IEEE Access*, vol. 6, pp. 34516–34526, 2018.

[37] S. J. Zhang, "A simplified real-time engine model for developing aeroengine control system," in *Proceedings of the 28th Joint Propulsion Conference and Exhibit*, Monterey, CA, USA, June 1992.

[38] M. Lichtsinder and Y. Levy, "Jet engine model for control and real-time simulations," *ASME J Eng Gas Turbines Power*, vol. 128, no. 4, pp. 745–753, 2004.

[39] G. Y. Chung, M. Dhingra, J. V. R. Prasad, R. Meisner, and S. Sirica, "An analytical approach to gas turbine engine model linearization," *ASME Turbo Expo*, vol. 3, pp. 105–115, 2011.

[40] X. Xu, T. H. Zhang, and H. L. Sheng, "Research on MTE real-time modeling based on dynamic coefficient method," *China Mechanical Engineering*, vol. 26, no. 2, pp. 243–247, 2015, in Chinese.

[41] A. Pandey, M. de Oliveira, and C. M. Holcomb, "Multi-stage system identification of a gas turbine," *ASME Turbomachinery Technical Conference and Exposition*, vol. 6, pp. 30–39, 2017.

[42] A. P. G. Mehrpanahi, M. Arbabtafti, and A. Hamidavi, "Semi-simplified black-box dynamic modeling of an industrial gas turbine based on real performance characteristics," *ASME Journal of Engineering Gas Turbines Power*, vol. 139, no. 12, pp. 121601–121612, 2017.

[43] M. B. Tischler and M. G. Cauffman, "Frequency-response methods for rotorcraft system identification: flight applications to BO-105 coupled rotor/fuselage dynamics," *Journal of the American Helicopter Society*, vol. 37, no. 37, pp. 3–10, 1992.

[44] D. C. Evans, D. L. Jones, and D. Rees, "Identifying linear models of systems suffering nonlinear distortions, with a gas turbine application," *IEE Proceedings - Control Theory and Applications*, vol. 142, no. 3, pp. 229–240, 1995.

[45] C. Evans, D. Rees, and A. Borrell, "Identification of aircraft gas turbine dynamics using frequency-domain techniques," *Control Engineering Practice*, vol. 8, no. 4, pp. 457–467, 2000.

[46] J. Schoukens, T. Dobrowiecki, and R. Pintelon, "Parametric and nonparametric identification of linear systems in the presence of nonlinear distortions-a frequency domain approach," *IEEE Transactions on Automatic Control*, vol. 43, no. 2, pp. 176–190, 1998.

[47] N. Liu, "Research on modeling in frequency domain and multivariable robust control for aircraft engine," Dissertation, Nanjing University of Aeronautics and Astronautics, Nanjing, China, 2015.

[48] K. Rodriguez-Vazquez and P. J. Fleming, "Multiobjective genetic programming for gas turbine engine model identification," in *Proceedings of the Control '98 UKACC International Conference*, pp. 1385–1390, Stevenage, UK, September 1998.

[49] C. Evans, P. J. Fleming, D. C. Hill et al., "Application of system identification techniques to aircraft gas turbine engines," *Control Engineering Practice*, vol. 9, no. 2, pp. 135–148, 2001.

[50] Y. Gao, J. Q. Wang, and B. Yu, "The implementation of embedded aircraft engine on-board model based on NARX technology," *Chinese Journal of Electron Devices*, vol. 39, no. 6, pp. 1440–1444, 2016, in Chinese.

[51] Z. P. Song, L. Cheng, and R. X. Wei, "A volterra progression model of nonlinearity dynamic respondence of aero engine," *Journal of Aerospace Power*, vol. 19, no. 4, pp. 577–580, 2004, in Chinese.

[52] J. Q. Wang, Z. F. Ye, and Z. Z. Hu, "On-board real-time modeling of aircraft engines with Hammerstein-Wiener representation," *Journal of Aerospace Power*, vol. 29, no. 10, p. 8, 2014, in Chinese.

[53] Z. Y. Wei, S. Jafari, S. G. Zhang, and T. Nikolaidis, "Hybrid Wiener model: an on-board approach using post-flight data for gas turbine aero-engines modelling," *Applied Thermal Engineering*, vol. 184, 2020.

[54] K. L. Cai, S. S. Xie, and Y. Wu, "Identification of aero-engines model based on T-S fuzzy model," *Journal of Propulsion Technology*, vol. 28, no. 2, pp. 194–198, 2007, in Chinese.

[55] L. Wang, S. S. Xie, Z. G. Miao, and L. T. Ren, "Identification of T-S fuzzy model for aero-engine based on flight envelop division," *Journal of Aerospace Power*, vol. 28, no. 5, pp. 1159–1165, 2013, in Chinese.

[56] R. Li, Y. Guo, S. K. Nguang, and Y. Chen, "Takagi-Sugeno fuzzy model identification for turbofan aero-engines with guaranteed stability," *Chinese Journal of Aeronautics*, vol. 31, no. 6, pp. 1206–1214, 2018, in Chinese.

[57] F. Qian and F. L. Deng, "Research on fuzzy markov model identification of aero-engine," *Journal of Northwestern Polytechnical University*, vol. 20, no. 1, pp. 113–116, 2002, in Chinese.

[58] S. S. Xie and S. Q. Fan, "The set-up of neural network identification model for aeroengine using inner product

principle," *Journal of Propulsion Technology*, vol. 19, no. 1, pp. 11–15, 1998, in Chinese.

[59] A. R. Tavakolpour-Saleh, S. A. R. Nasib, A. Sepasyan, and S. M. Hashemi, "Technology parametric and nonparametric system identification of an experimental turbojet engine," *Aerospace Science and Technology*, vol. 43, pp. 21–29, 2015.

[60] J. C. Lopes and A. E. Ruano, "Identification of aircraft gas-turbine dynamics using B-splines neural networks," *Ifac Workshop on Algorithms and Architectures for Real-Time Control*, vol. 33, no. 6, pp. 123–128, 2000.

[61] K. F. Ding and F. S. Qi, "An identification model of aero-engine based on the RBF network," *Journal of Aerospace Power*, vol. 15, no. 2, pp. 205–208, 2000, in Chinese.

[62] X. K. Wei, Y. H. Li, J. Y. Wang, and P. Zhang, "A novel aero-engine identification model based on support vector machines," *Journal of Aerospace Power*, vol. 19, no. 5, pp. 684–688, 2004, in Chinese.

[63] H. T. Wang, S. S. Xie, W. Wu, and Z. G. Miao, "Dynamic process identification of aircraft engine based on a novel sparse least square support vector machines," *Journal of Aerospace Power*, vol. 25, no. 9, pp. 2139–2147, 2010, in Chinese.

[64] G. Alag and G. Gilyard, "A proposed Kalman filter algorithm for estimation of unmeasured output variables for an F100 turbofan engine," in *Proceedings of the 26th Joint Propulsion Conference*, Monterey, CA, USA, June 1990.

[65] J. S. Orme and T. R. Conners, "Supersonic flight test results of a performance seeking control algorithm on a nasa f-15 aircraft," in *Proceedings of the 30th Joint Propulsion Conference*, Indianapolis, IN, USA, June 1994.

[66] D. J. Malloy, A. T. Webb, and D. S. Kidman, "F-22/F119 propulsion system ground and flight test analysis using modeling and simulation techniques," *ASME Turbo Expo*, vol. 1, 2002.

[67] N. Sugiyama, "System identification of jet engines," *ASME Journal of Engineering for Gas Turbines and Power*, vol. 122, no. 1, p. 7, 1998.

[68] T. H. Chen, "On-board real-time adaptive modeling and high stability control technology of aero-engine," Dissertation, Nanjing University of Aeronautics and Astronautics, Nanjing, China, 2010.

[69] H. B. Zhang, F. Ye, Y. J. Li, and G. Q. Chen, "Semi-physical simulation on integrated helicopter/engine control system," *Journal of Aerospace Power*, vol. 28, no. 7, pp. 1650–1658, 2013.

[70] Q. Zheng, H. Zhang, Y. Li, and Z. Hu, "Aero-engine on-board dynamic adaptive MGD neural network model within a large flight envelope," *IEEE Access*, vol. 6, pp. 45755–45761, 2018.

[71] T. Brotherton, A. Volponi, R. Luppold, and D. L. Simon, "eSTORM: enhanced self tuning on-board real-time engine model," in *Proceedings of the IEEE Aerospace Conference*, Big Sky, MT, USA, March 2003.

[72] A. Volponi, T. Brotherton, and R. Luppold, "Empirical tuning of an on-board gas turbine engine model for real-time module performance estimation," *ASME J Eng Gas Turbines Power*, vol. 130, no. 2, Article ID 021604, 2008.

[73] A. Volponi, "Enhanced self tuning on-board real-time model (eSTORM) for aircraft engine performance health tracking," Report No NASA/CR-2008-215272, Lewis Research Center, Cleveland, OH, USA, 2008.

[74] F. Lu and J. Q. Huang, "AGA-LSSVR compensation for on-board self tuning model of aero-engine model," *Journal of Aerospace Power*, vol. 24, no. 4, pp. 880–885, 2009, in Chinese.

[75] Y. Liu, "Intelligent fault-tolerant control system design and hardware-in-the-loop simulation validation of a turbofan engine," Dissertation, Nanjing University of Aeronautics and Astronautics, Nanjing, China, 2016.

[76] H. Yao, *Full Authority Digital Electronic Control System for Aero-Engine*, Aviation industry press, Beijing, China, 2014, in Chinese.

[77] S. J. Li, J. B. Tian, D. Q. Cao, H. X. Wang, and S. Wu, "Implementation of automatic control system for iron bird hydraulic system test," *Aviation Precision Manufacturing Technology*, vol. 48, no. 6, pp. 29–32, 2012, in Chinese.

[78] T. Tagashira, T. Mizuno, M. Koh, and N. Sugiyama, "ATF test evaluation of model based control for a single spool turbojet engine," *ASME Turbo Expo*, vol. 1, pp. 673–685, 2009.

[79] W. Fuller, "Constrained dynamic inversion control and its application to turbomachinery," Report No.: 2010-01-1737, Lewis Research Center, Cleveland, OH, USA, 2010.

[80] J. Orme and G. Schkolnik, "Flight assessment of the on-board propulsion system model for the performance seeking control algorithm on an f-15 aircraft," Report No.: NASA TM-4705, Lewis Research Center, Cleveland, OH, USA, 1995.

[81] K. Lietzau and A. Kreiner, "Model based control concepts for jet engines," *ASME Turbo Expo*, vol. 8, pp. 9–16, 2001.

[82] M. Lipperheide, F. Weidner, M. Wirsum, M. Gassner, and S. Bernero, "Long-term NOx emission behavior of heavy duty gas turbines: an approach for model-based monitoring and diagnostics," *ASME Journal of Engineering Gas Turbines Power*, vol. 140, no. 10, Article ID 101601, 2018.

[83] A. Nannarone and S. A. Klein, "Start-up optimization of a CCGT power station using model-based gas turbine control," *ASME Journal of Engineering Gas Turbines Power*, vol. 141, no. 4, Article ID 41018, 2018.

[84] T. Kobayashi and L. S. Donald, "Hybrid kalman filter approach for aircraft engine in-flight diagnostics: sensor fault detection case," *ASME Journal of Engineering Gas Turbines Power*, vol. 129, no. 3, pp. 745–754, 2006.

[85] J. V. Allan, "Gas turbine engine health Management_Past present and future trends," *ASME Journal of Engineering Gas Turbines Power*, vol. 136, no. 5, pp. 433–453, 2013.

[86] C. X. Lan and J. G. Sun, "An analytical redundancy technology based on a component tracking filter," *Journal of Aerospace Power*, vol. 9, no. 3, pp. 289–292, 1994, in Chinese.

[87] X. H. Huang, "Aeroengine virtual sensor based on fuzzy logic," *Journal of Nanjing University of Aeronautics & Astronautics*, vol. 37, no. 4, pp. 447–451, 2005, in Chinese.

[88] F. Lu, Jq Huang, Cs Ji, Dd Zhang, and Hb Jiao, "Gas path on-line fault diagnostics using a nonlinear integrated model for gas turbine engines," *International Journal of Turbo and Jet Engines*, vol. 31, no. 3, in Chinese, 2014.

[89] V. Panov, "Integrated model-based control and health management for industrial gas turbines," in *Proceedings of the IEEE International Conference on Prognostics and Health Management*, Detroit, MI, USA, June 2016.

[90] S. Garg, "Aero-propulsion control research in support of NASA aeronautics research strategic thrusts," in *Proceedings of the 2018 Joint Propulsion Conference*, Cincinnati, OH, USA, July 2018.