



A novel deep multimodal information fusion model for aero-engine state prediction

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Abstract

Condition monitoring plays an important role in the safety and reliability of aero-engine. In this paper, a novel deep multimodal information fusion (MIF) method is proposed, which integrates information from the physical-based model and the data-driven model. Two deep Boltzmann machines are constructed for feature extraction from sensor data and model simulation data, respectively. Whereby information from these two modalities is mapped into a high-dimensional space and forms a joint representation, and then combined with a multi-layer feedforward neural network to form the MIF model for real-time performance simulation and prediction. Compared with the traditional single-modality method, the proposed method fuses the information of two key modalities. The experimental results indicate that proposed method improves the accuracy of engine parameters prediction.

Keywords: Condition monitoring, aero-engine, information fusion

1. Introduction

Aero-engine is the core mechanical system that operates in harsh environment and extreme conditions. Throughout the service life, aero-engine will inevitably degradation, leading to abnormalities and unexpected failures, which seriously threaten its reliability [1-3]. Therefore, the construction of a high-accuracy model is essential for operational safety and is the basis for further development of engine health management system [4-5].

Modern civil aircraft will collect thousands of flight parameters in real time and some of them even have a sampling frequency of 32Hz. For civil aero-engine, on-board parameters mainly include inlet environmental parameters, thermodynamic parameters of gas components, mechanical vibration parameters and oil system parameters. Due to the complex flight environment and the inherent limitations of sensors, on-board measured data may be affected by sensor failures and acquisition errors. Moreover, dynamic performance models, an important tool for engine simulation, are often simplified, which leads to different characteristic errors at different flight phases. Thus, the traditional model-based methods (MBMs) are difficult to meet the high-accuracy requirements, and it is prone to the model-engine mismatch.

In recent years, artificial intelligence has gradually become a research hotspot in the field of aero-engine performance prediction. The development of artificial intelligence has experienced early artificial intelligence represented by expert systems, to machine learning represented by various intelligent algorithms, and then to deep learning represented by deep neural networks. Where machine learning achieves the combination of algorithms and data, the effectiveness of the model depends not only on the correct choice of algorithms, but also on the quality and efficient representation of the data. It is generally believed that data and feature representation determine the upper limit of machine learning, and good models and algorithms only approximate this upper limit. In machine learning, feature extraction is mainly carried out by relying on artificial experience and prior knowledge, also known as feature engineering, which is suitable for situations with small amounts of data. When entering the era of deep learning with big data as a prominent feature and subsequent artificial intelligence, feature engineering has been difficult to meet the demand for efficient feature extraction of large amounts of data. At the first ICLR meeting in 2013, representation

learning was proposed, which does not rely on manual experience, can automatically simplify massive and complex original data, eliminate invalid, redundant and even harmful information, and refine effective information to form features. Further combined with tasks such as classification or regression of artificial intelligence algorithms to achieve better model effects.

With the development of advanced sensor technology and intelligent algorithms, data-driven methods (DDMs) have gained more attention, such as artificial neural network (ANN), support vector machine (SVM) and deep learning, which do not require detailed mechanism knowledge of the engine [6-10]. Lu et al [3]. proposed a kernel extreme learning machine for engine fault diagnosis. Wang et al [11]. proposed a data-driven strategy for aero-engine degradation prognostic. The significant advantage of the DDM is that it can learn information from raw big data about the current state of the engine. However, noisy data and redundant information will inevitably interfere with the performance of the DDM. In addition, the DDM ignores the physical meaning of the data, resulting in insufficient generalization performance [12].

In this paper, a novel deep multimodal information fusion (MIF) method is proposed by combining the advantages of MBM and DDM, which is applied to the real-time performance simulation and prediction of civil aero-engines.

2. Methodology

The structure of the proposed Deep multimodal information fusion (MIF) model is shown in figure 1, which consists of two (deep Boltzmann machine) DBM networks and an multilayer feedforward neural network (MFNN). Compared with traditional neural networks, DBM is a deep learning model with strong representation learning and classification ability. DBM 1 represents the DDM, which learns and extracts features from the original noisy sensor data of the engine. And the input information of DBM 2 is the simulation results of PBM. We expect to jointly represent PBM information and original data information in a high-dimensional space by combining DBM 1 and DBM 2. Then, the MFNN network is used to learn and classify the joint representation information, so as to realize the detection and isolation of engine faults.

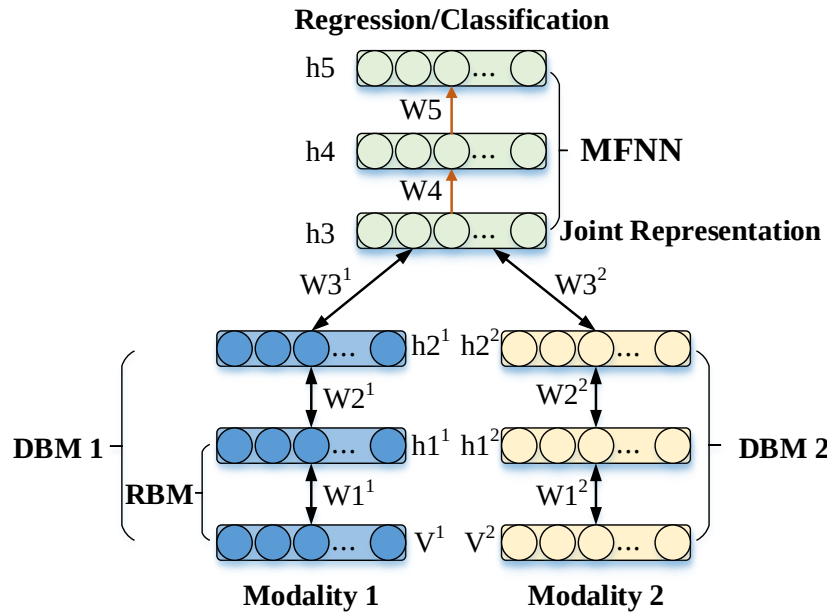


Figure 1 The graphical model of the MIF model for two modalities.

DBM is composed of multiple restricted Boltzmann machines (RBMs), where each layer captures the complex and higher-order correlations between hidden features in the layer below. RBM is a generative stochastic neural network proposed by Hinton and Sejnowski in 1986. An RBM is an undirected graphical model with one visible unit layer vRD and one hidden unit layer hRF . Each visible unit is connected with each hidden unit, and the units in the layer are independent of each other. There is no edge connection between visible and hidden elements, and both visible and hidden variables are binary variables with state $\{0,1\}$. The Contrast Divergence (CD) algorithm was used to

estimate the parameters and determine the weight and bias vector.

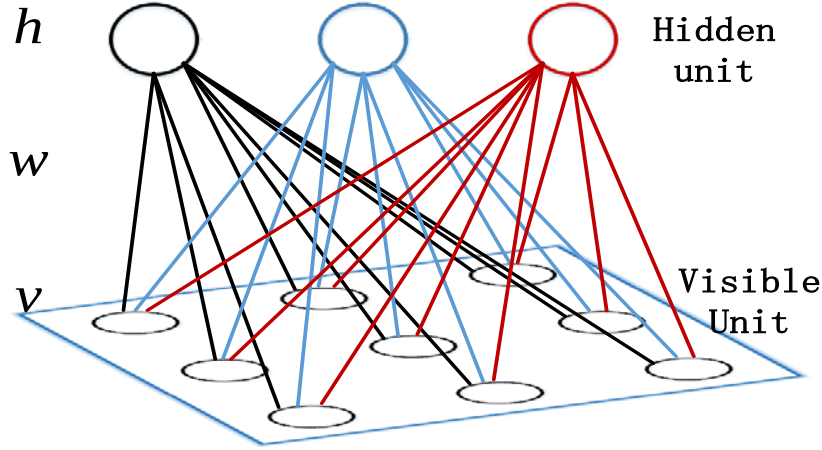


Figure 2 RBM network structure diagram.

RBM was originally developed for binary-valued data, the model defines the energy function E as follows:

$$E(\mathbf{v}, \mathbf{h}) = -\sum_i^D a_i v_i - \sum_j^F b_j h_j - \sum_i^D \sum_j^F v_i w_{ij} h_j \quad (1)$$

Where a_i and b_j are the biases of the visible unit v_i and the hidden unit h_j respectively. W_{ij} is the weight matrix of v_i and h_j .

Considering that the Gaussian RBM model is more appropriate to modeling real-valued sensor data, and its energy function is as follows:

$$E(\mathbf{v}, \mathbf{h}) = -\sum_i^D \frac{(v_i - a_i)^2}{2\sigma_i^2} - \sum_j^F b_j h_j - \sum_i^D \sum_j^F \frac{v_i}{\sigma_i} w_{ij} h_j \quad (2)$$

Where σ_i is the standard deviation of the Gaussian noise at the input node i . The joint probability distribution $p(\mathbf{v}, \mathbf{h})$ of $\mathbf{v}$ and $\mathbf{h}$ is defined as:

$$p(\mathbf{v}, \mathbf{h}) = \frac{1}{Z} \exp(-E(\mathbf{v}, \mathbf{h})) \quad (3)$$

Where $Z = \sum_{\mathbf{v}, \mathbf{h}} \exp(-E(\mathbf{v}, \mathbf{h}))$ is the partition function.

The conditional probability of the visible layer and hidden layer is:

$$p(h_j = 1 | \mathbf{v}) = \text{sigmoid} \left(b_j + \sum_i^D \frac{v_i}{\sigma_i} w_{ij} \right) \quad (4)$$

$$p(v_i | \mathbf{h}) = N(a_i + \sigma_i h_j w_{ij}, \sigma_i^2) \quad (5)$$

Where $\text{sigmoid} = 1/(1 + \exp(-x))$, $N(\mu, \sigma^2)$ denotes Gaussian distribution with mean μ and variance σ^2 . The model parameters are updated as follows:

$$\Delta w_{ij} = \varepsilon \left(\text{Ep}_{\text{data}} \left(\frac{1}{\sigma_i} v_i h_j \right) - \text{Ep}_{\text{model}} \left(\frac{1}{\sigma_i} v_i h_j \right) \right) \quad (6)$$

$$\Delta a_{ij} = \varepsilon \left(\text{Ep}_{\text{data}} \left(\frac{1}{\sigma_i^2} v_i \right) - \text{Ep}_{\text{model}} \left(\frac{1}{\sigma_i^2} v_i \right) \right) \quad (7)$$

$$\Delta b_{ij} = \varepsilon \left(\text{Ep}_{\text{data}}(h_j) - \text{Ep}_{\text{model}}(h_j) \right) \quad (8)$$

Where ε is the learning rate, $\text{Ep}_{\text{data}}(\cdot)$ represents the expectation of $p(\mathbf{h} | \mathbf{v})$ given the input data, and $\text{Ep}_{\text{model}}(\cdot)$ represents the expectation of $p(\mathbf{v}, \mathbf{h})$ given the model.

3. Proposed model structure

Based on the proposed deep multimodal information fusion (MIF) method, this paper fuses airborne data and simulation data to achieve key parameter prediction in engine health diagnosis. Figure 3

shows the logical relationship of the research content, which mainly includes flight data preprocessing, multimodal information fusion model construction and error comparison analysis.

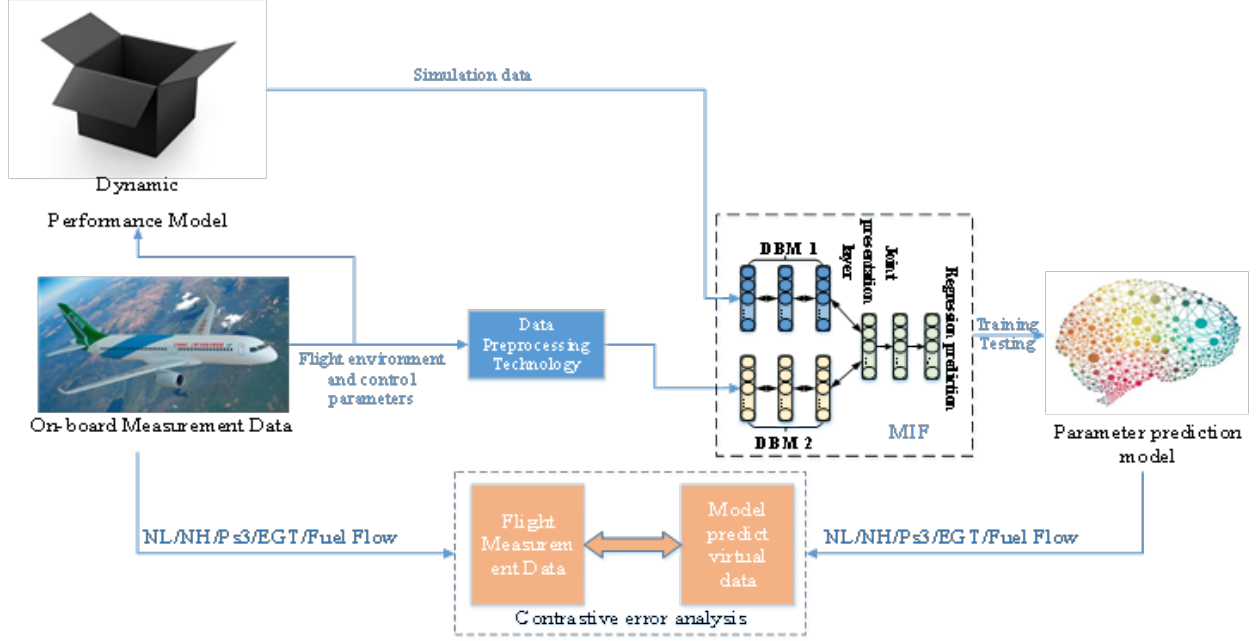


Figure 3 The framework for information fusion simulation system.

4. Experimental study

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4.1 Error analysis of flight simulation data

Before the error analysis, this study conducted the detection of duplicate data on the original data based on the Sorted Neighborhood Method (SNM). The research idea is as follows: First, the key values used in data set sorting are determined according to the knowledge and experience of experts in the data field. In this paper, since the flight data is time series data and there are no other attribute values, the data at a certain moment is randomly selected as the key values. Secondly, traverse the data set and generate sorting key values for each record; Then, the records are sorted according to the key values of the records, so that different duplicate records are theoretically located near each other after sorting. Finally, a fixed size sliding window is used for repeated detection of the data set. The principle of sliding window is shown in the following figure. The original flight data in this paper includes environment and engine related information, a total of 68 parameters are derived, and the sliding window size is set to 12 in the SNM.

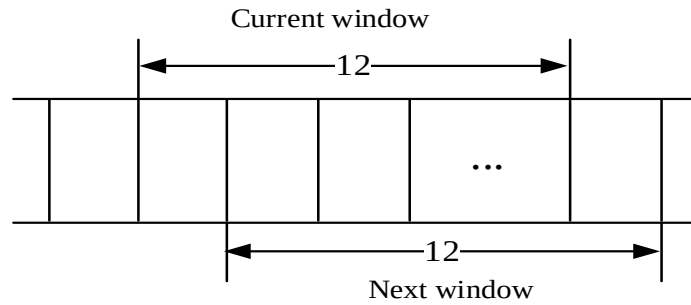


Figure 4 Sliding window mode.

Generally speaking, the dynamic performance model of aero-engine is provided to the user together with the engine, but this kind of performance simulation model can not fully match the actual engine to some extent. On the one hand, the model is built on the basis of many idealized assumptions,

such as the gas is regarded as a complete gas and treated in one dimension, ignoring complex combustion and heat transfer models. On the other hand, the engine will deteriorate during use, causing the performance to deviate from the ideal design state. Therefore, there are complex errors between the dynamic performance model and the actual data.

The simulation error of the model is closely related to the engine working state, which usually corresponds to the different flight phases in the flight cycle, that is, including Taxi out/Take off, Climb, Cruise, Descent, Landing/Taxi in. Therefore, it is necessary to study the division rules first, and divide the flight phases of the original flight data. Civil airliners have their own flight phase division standards according to different aircraft types, it is necessary to divide flight stages. The general principle is to delineate the flight phase according to the parameter values such as pressure altitude (PA), airspeed and their conversion values, in order to facilitate the program to automatically divide the flight phases of all flight data files in batches, the quantitative division criteria are required, according to a large number of tests and reference related data, the quantitative classification criteria determined in this paper are mainly based on the barometric altitude and its first derivative, airspeed and its first derivative. The flight phases divided in are shown in Figure 5.

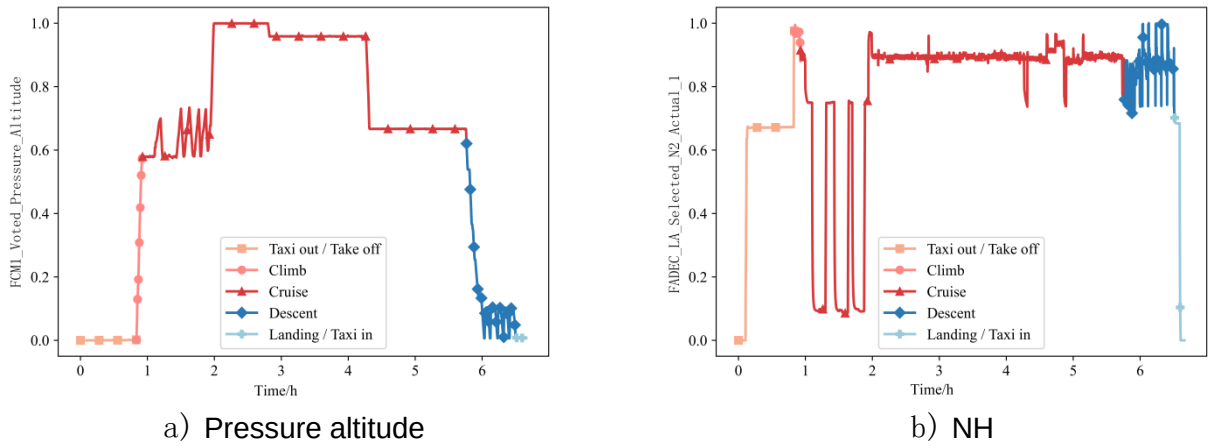
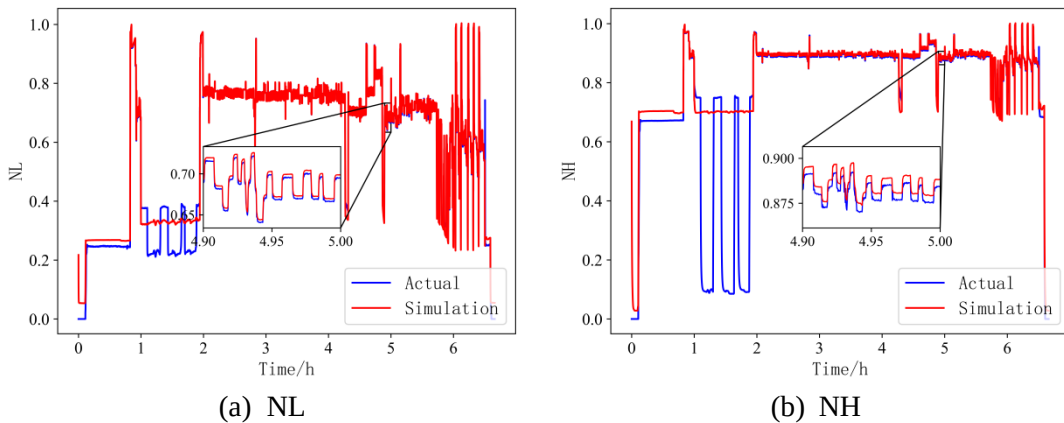
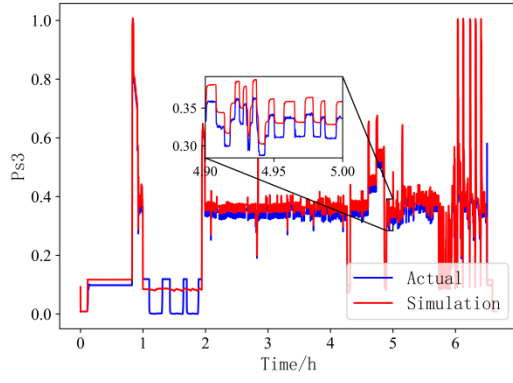


Figure 5 Flight phase division and flight cycle parameter change. (The parameters are normalized).

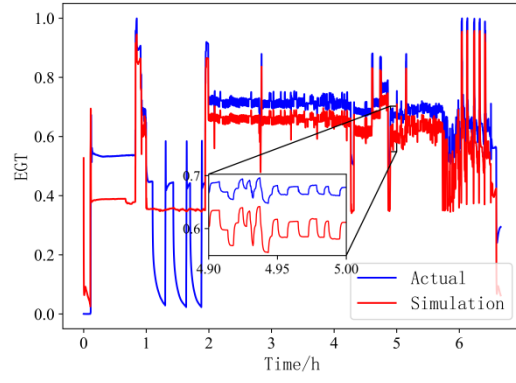
How to deal with the inevitable simulation error of dynamic performance model is a difficult point in the current flight, and the error always has different characteristics at different flight states. In general, the deviation in steady-state operation is constant, while the error in dynamic-state operation has a hysteresis, and the change of bleed air state will also cause obvious effects.

In this paper, data during a flight cycle was selected, and the error analysis was carried out for five key parameters: NL, NH, Ps3, EGT and Fuel Flow. Data for five parameters selected was standardized, and are shown in figure 6. All parameters were named in the same manner as other sections in this paper.

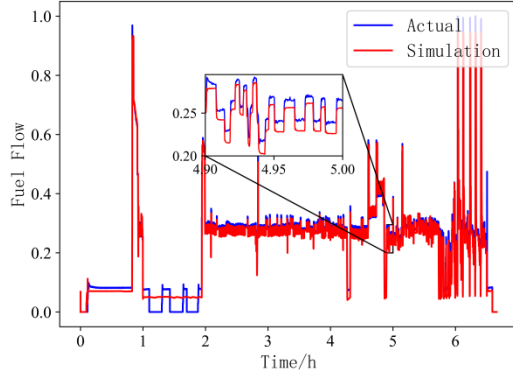




(c) Ps3



(d) EGT



(e) Fuel Flow

Figure 6 Simulation error analysis of five key engine parameters during a flight cycle.

As can be seen from the above figure, there is a large deviation at the starting point, which is due to the incomplete initialization of the simulation model. In the early stage of the flight cycle, the bleed air state changes drastically, the simulation error of each parameter is also very large, and the changing trend between the two is basically the same. In the middle stage, an approximate constant deviation occurs. During this period, the error degree of each parameter is different, and the error of Ps3 and EGT is the most obvious. In the late flight phase, the operating condition of engine changes at a very high frequency, and the simulation error also changes synchronously.

Generally, cruise status accounts for more than 65% of the entire flight cycle, and it is a critical flight period. So, in this paper, cruise status with normal bleed air (1 state) was selected as the subject, and conducts a comparative analysis of the error of the data at this stage, as shown in Figure 7.

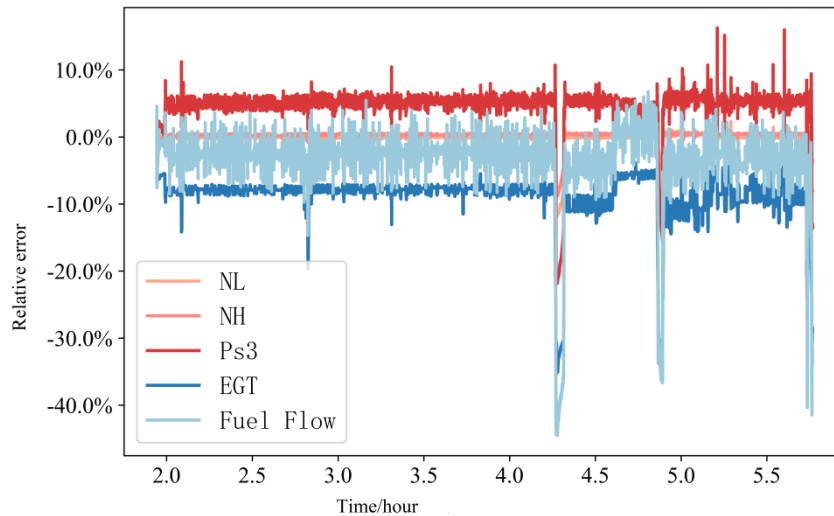


Figure 7 Simulation error comparison of flight parameters in cruise phase.

Table 1 shows the error of each parameter, including average relative error, MSE and MAE.

Table 1. Statistical results of flight parameter simulation error in cruising phase.

parameter	NL	NH	Ps3	EGT	Fuel Flow
Average relative error (%)	-0.15	0.21	4.65	-8.71	-3.31
MSE	0.21	0.59	98.76	3322.09	6761.11
MAE	0.12	0.42	9.79	55.15	71.20

4.2 High-precision simulation based on MIF method

Based on big flight data, this paper constructs the deep multimodal information fusion (MIF) model, and the data used for modeling and verification are detailed described in table 2.

Table 2. Sample description of flight data used for modeling and verification.

training sample				test sample		
Flight circle	Flight Time	Sampling frequency	Sampling point	Flight circle	Flight Time	Sampling frequency
7	21.9h	32Hz	252 million	1	6.67h	32Hz

In order to validate the effects, four different data-driven models are used to compare. We set four types of model architectures according to different data sources, as shown in table 3, and the model architecture is shown in figure 8.

Table 3. Four modeling architectures based on multi-source data.

Data source	Model architecture	remark
1	DBM1+MLPRegressor	
2	DBM2+MLPRegressor	
3	DBM1+MLPRegressor	
12	DBM1+DBM2+MLPRegressor	The proposed MIF architecture

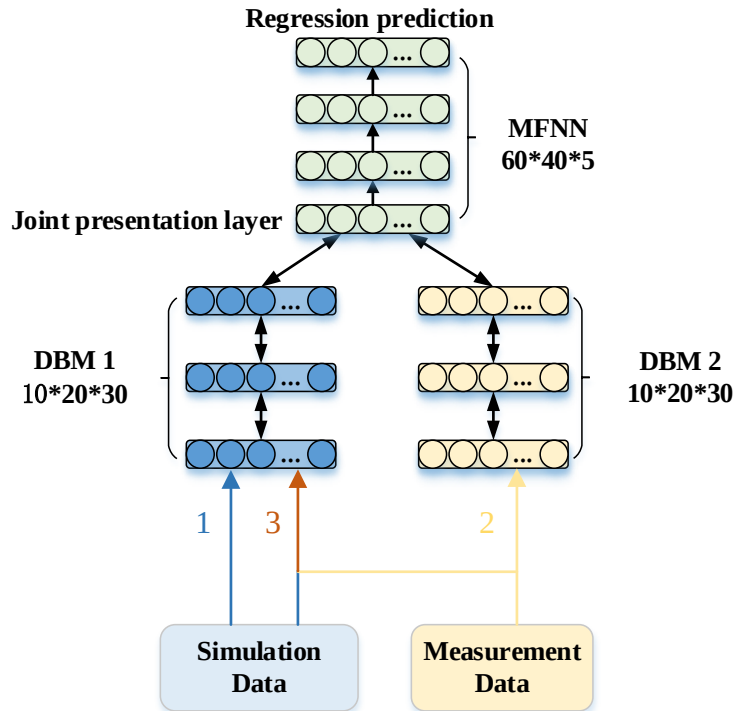


Figure 8 Model architecture for key engine parameter prediction.

Model testing results MSE are given in table 4. Compared with original simulation error, model 1 and

2 generally do not have a great improvement, which indicates that dynamic simulation data and flight data contain different information, and neither can fully map the engine state. The prediction accuracy of model 3 and model 12 has been significantly improved, and the effect of model 12 is even better. The error of five parameters is reduced by more than 44.1%, especially the error of Ps3 and EGT is reduced by 93%, which reflects the obvious advantages of the proposed multimodal information fusion method.

Table 4. Model testing error analysis (MSE).

Data source	NL	NH	Ps3	EGT	Fuel Flow
original simulation	0.21	0.59	98.76	3322.09	6761.11
1	0.26	0.17	4.49	374.79	7754.56
2	3.53	1.01	47.38	558.28	12142.51
3	0.32	0.12	6.49	278.13	2993.00
12	0.09	0.13	6.26	233.42	3781.70
decrease (12 vs original)	55.5%	77.5%	93.7%	93.0%	44.1%

Table 5 shows the MAE values of the statistical prediction results, and the outlier error of MAE is more robust than that of MSE. As can be seen from the table, the proposed No. 12 modeling scheme has a good effect on the prediction of other parameters except NL, and the NL prediction error does not decrease mainly because the original simulation error is small, which is difficult to further improve on this basis.

Table 5. Model testing error analysis (MAE).

Data source	NL	NH	Ps3	EGT	Fuel Flow
original simulation	0.12	0.42	9.79	55.15	71.20
1	0.35	0.22	1.44	15.88	67.94
2	0.57	0.41	4.36	17.40	50.28
3	0.52	0.29	2.07	14.20	41.91
12	0.19	0.29	2.20	13.93	51.08
decrease (12 vs original)	-51%	30%	77%	75%	28%

Furthermore, the flight data of cruising phase, the original dynamic simulation data and the prediction data of the proposed model 12 are contrasted, as shown in figure 9. As can be seen in this figure, the proposed multimodal information fusion model has higher accuracy than the original dynamic model during the whole flight phase, and it greatly improves the effect of engine parameter prediction.

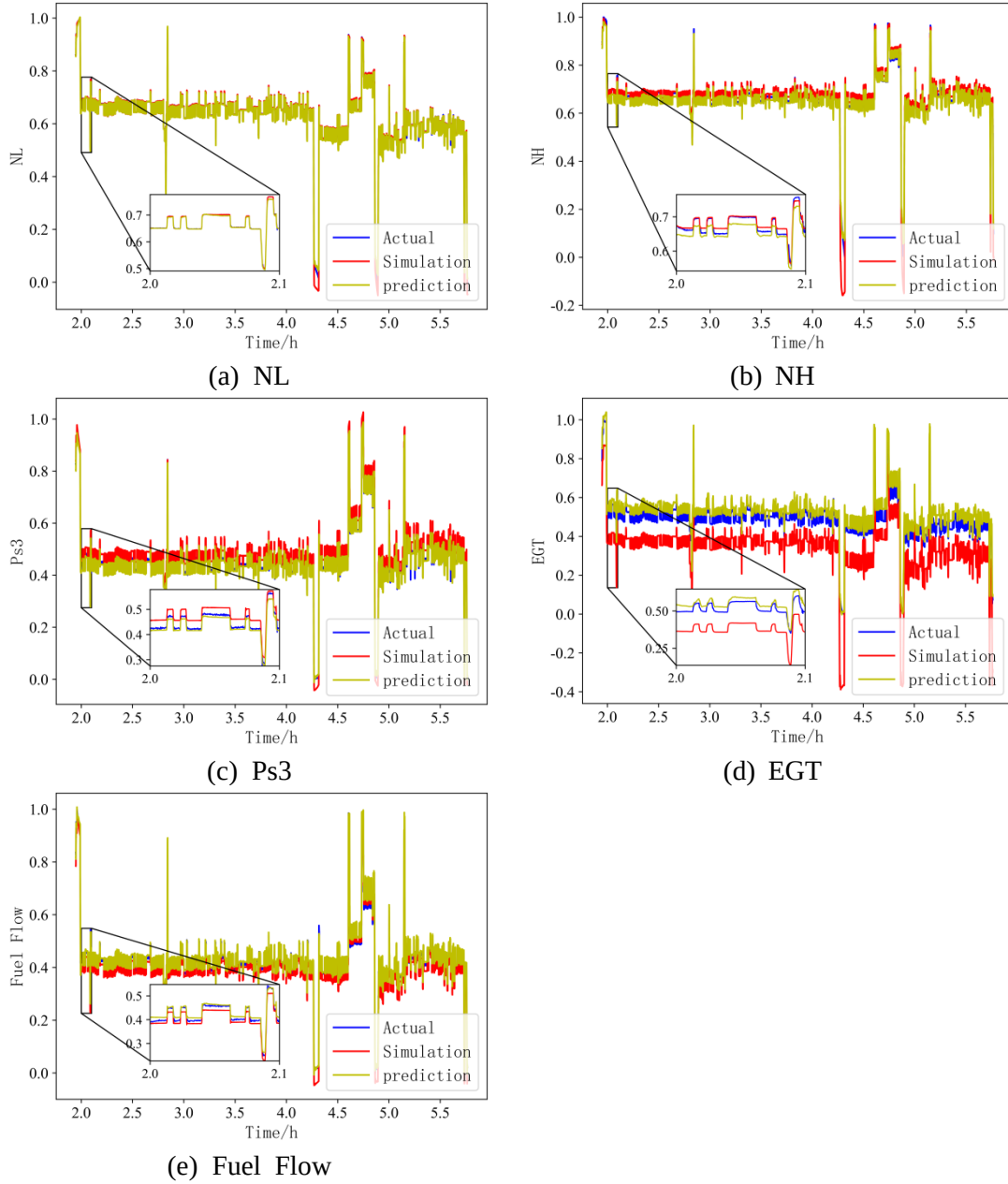


Figure 9 Validation test comparison

5. Conclusion

In this paper, a novel deep multimodal information fusion (MIF) method is proposed, which can be applied to the error correction of civil flight big data. Paper mainly focuses on error analysis and information fusion model construction. The main research results are as follows:

- (1) The simulation error varies in different flight phases and different operating states. A procedure for automatic division of flight phases was developed, which is based on characteristic parameters such as pressure altitude and flight speed. The error analysis between simulation data and flight data was carried out for five key engine parameters: NL, NH, Ps3, EGT and Fuel Flow. This provides a basis for the data selection of multimodal information fusion model.
- (2) High-precision regression prediction of NL, NH, Ps3, EGT and Fuel Flow was carried out based on the deep multimodal information fusion model and its basic architecture. This study compares four models from different data sources, and the final results show that the proposed method is superior.

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