Aeroengine Remaining Life Prediction Algorithm Based on Improved Differential Time Domain Features and LSTM

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Abstract. **In order to ensure the continuous airworthiness of the engine, airlines must carry out maintenance, repair and overhaul of the engine. This paper studies the prediction of the residual life of the aeroengine based on the improved differential time domain feature and LSTM, and analyzes the prediction framework, model and related algorithms of the residual life of the aeroengine based on the improved differential time domain feature and LSTM. This paper builds an engine life prediction algorithm DTF-LSTM based on improved differential time-domain features (DTF) and LSTM network. The network directly enhances the inheritance of historical output information by adding linear connections between adjacent output layers. The abstract local features extracted by LSTM are used as the input of the regression to predict the remaining life of the aero-engine. The predicted value of DTF-LSTM is close to the real value, and fitting the predicted value can obtain the residual service life curve of the aero-engine, which can accurately judge the degree of bearing degradation.**

Keywords: DTF-LSTM; Aeroengines; Residual life prediction

I. Introduction

For the aviation industry, the reliability management of the aviation engine is a very important link, therefore, it is more and more important to make objective and scientific prediction of the remaining life of the aviation engine. The difficulty lies in two aspects: first, how to comprehensively utilize less fault information and abundant state monitoring data; The second is how to deal with the diversity of failure modes caused by system complexity and the problems of improved differential time domain characteristics and LSTM. Engineering practice shows that LSTM technology can effectively reduce the probability of equipment failure and maintenance costs, especially in areas with high safety and reliability requirements (such as aerospace, wind power generation, weapons and equipment, etc.), which can significantly reduce the number of system outages and improve the success rate of tasks [1]. Liu et al [2] used LSTM's non-linear processing capability and combined with LSTM to carry out threshold monitoring on a single parameter to guide component maintenance. In addition, literature [3] has also conducted a large number of studies on different EGT (Exhaust Gas Temperature) prediction problems. In this paper, the working principle of the aero-engine gas circuit system is analyzed, and the asymptotic continuity of its state change is obtained, which is verified by the exhaust temperature data. In this paper, LSTM with long-term and short-term memory capability is used as the regression, and the abstract local features extracted by LSTM are used as the input of the regression, so as to predict the remaining life of the aeroengine. Considering the stability of the output, LSTM is used for automatic filtering of the output.

II. Engine Residual Life Prediction Method Based on Improved Differential Time Domain Features and LSTM

A. Treatment of gross errors.

EGTM data comes from sensors installed on the engine and enters the performance monitoring system through air-to-ground data link, message analysis program and other steps. All feature spaces are combined along the sensor data dimension to generate a new sequence as the input of the next LSTM. LSTM realizes selective memory of past information by building memory blocks in the model, overcomes the problem of gradient explosion or gradient disappearance during training of standard RNN (Recurrence Neural Networks), and can realize long-term memory of past information. The engine limit temperature is determined by the manufacturer according to the temperature limit that the material of key components can bear, and EGTM will gradually increase with the increase of flight time. This kind of uncertainty is reflected in the deviation of monitoring parameters, the uncertainty of monitoring information and the uncertainty in system reliability analysis. When faced with complex flight conditions and the pilot's control is fierce, its state always gradually reaches the final state in the form of continuous slight changes [4]. It reflects the running status of the aero-engine under the current sortie and is an important data source for monitoring the status of the aero-engine. However, these original data often contain the key characteristics of the degradation process of equipment system performance. Comprehensive utilization of a large number of state detection data, reasonable assessment of the degradation of aircraft engines, so as to achieve the prediction of its remaining life.

B. Gated recursive unit.

LSTM can produce many variants by changing the data transmission mode between gate structures or changing the gate structure. Among various variants, cell state is mostly added to different gate structures through peephole, or the combination of forgotten gate and input gate is forgotten [5]. One or more future values of EGTM are predicted by inputting several current or historical data of EGTM (exhaust gas temperature margin). If the degradation mode of EGTM can be obtained, it will be easy to predict the remaining life of the engine from the

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perspective of performance degradation. The rotation, wear or damage of the engine rotor will produce a certain degree of vibration signals. By observing the vibration levels of the high and low pressure rotors and their components of the engine.

The forgetting gate is used to output a number $f(z)$ between 0 and 1 by reading $t(z-1)$ and $y(z)$. this number will determine the retention degree of $R(z-1)$. the calculation formula is:

$$f(z)=\gamma[E_f t(z-1)+R_f y(z) v_f] \tag{1}$$

The function of the input gate is to determine which new information will be transmitted to the cell state in $t(z-1)$ and $y(z)$. the specific data processing is divided into two parts. the first part determines which values to update by using Sigmod activation function, and the second part adds $b(z)$ to the cell state by using tanh activation function. the calculation formula is [6]:

$$n(z)=\gamma[E_n t(z-1)+R_y(z)+v_n] \tag{2}$$

$$b(z)=\tan t[E_b t(z-1)+R_b y(z)+v_b] \tag{3}$$

We can judge the degradation of the aero-engine by the magnitude of this value, and then calculate the related degradation rate through the calculation formula for different degradation modes. The forward differential value of sensor monitoring data under the same operation mode and the accumulated value of different operation modes are added into the feature set, and the data set is expanded on the basis of the original flight parameter data to further mine the flight parameter data information. The output of the node will be fed back to itself and participate in the calculation of the next moment. This feedback is called "state" or "memory" in RNN and is the core of RNN. Before predicting the remaining life, the output of GRU(Gated Recurrent Units) is filtered by several layers of LSTM to improve the stability of the predicted output.

C. DTF-LSTM

This paper builds an engine life prediction algorithm DTF-LSTM based on improved DTF (differential time-domain features) and LSTM network. By fusing its abundant state monitoring data, the functional relationship between cumulative degradation and monitoring parameters is established by using relevant calculation formulas, and then the expected value and variance value are calculated. Therefore, the cumulative degradation of the engine can be judged by periodically detecting whether the changes of these state parameters exceed the standard through the state monitoring program in the maintenance strategy. The distance measurement between the two EGTM time series data should meet the following requirements: it is not sensitive to short-term fluctuations and can reflect the consistency of long-term trends. LSTM module analyzes and processes the preprocessed EGTM data, explores the change rule of EGTM with the running time of the aircraft and predicts the value of EGTM in the future.

Absolute deviation is used for deviation calculation of aeroengine EGTM data, and the calculation formula is as follows:

$$\Delta EGTM = EGTM_O - EGTM_Y \tag{4}$$

Where, the unit is°C, O represents the conversion value, and Y represents the baseline value.

The standardization of EGTM data of aero-engine is carried out by min- max standardization method, and the calculation formula is as follows:

$$T_i = Z_i - Z_{\min} / Z_{\max} - Z_{\min} \tag{5}$$

Where T_i is the original EGTM data and Z_i is the value of the original EGTM data after min- max standardization.

No matter what kind of variation, the main feature of LSTM is that each new input contains some features of the previous input. The final model is simpler than the standard LSTM model and is the most popular variant of LSTM. The difference is that the parameters of each moment of the circulating neurons in RNN are shared, so the calculation of gradient depends on the gradient of all previous moments. By introducing the difference time domain feature, the time relation between monitoring values is strengthened, and the accurate prediction of aero-engine performance degradation is realized by training large sample flight parameter data. According to the cumulative degradation value and diversified monitoring data, the degradation degree of the aero-engine can be calculated directly through the calculation formula after inputting new monitoring data.

III.TF-LSTM Model Case Validation Analysis

In the validation of DTF-LSTM model, EGTM data of an aeroengine is selected for validation analysis [7]; The sampling period of the EGTM data is 100 flight cycles. In this paper, 66 EGTM data are used in the first 13400 cycles of the aeroengine. The sliding time window method is used to consider the monitoring data at multiple times, and DTF-LSTM is used to capture the hidden time series features in the data. According to the accumulated value of the operation modes, the difference between the sensor monitoring value under the current mode and the sensor monitoring value under the same operation mode at the previous moment is calculated. According to the order of the magnitude of the correlation coefficient from small to large, the preselected features are sorted, and scoring values of 1 to 10 are respectively assigned; Then, the linear and nonlinear correlation score values are added to obtain the total score of preselected features. The training of the model is completed through the training set, and the trained model is used to predict the degradation degree of subsequent bearings. After completing the training of the network, the output of DTF-LSTM to the training set and test set is shown in fig. 1.

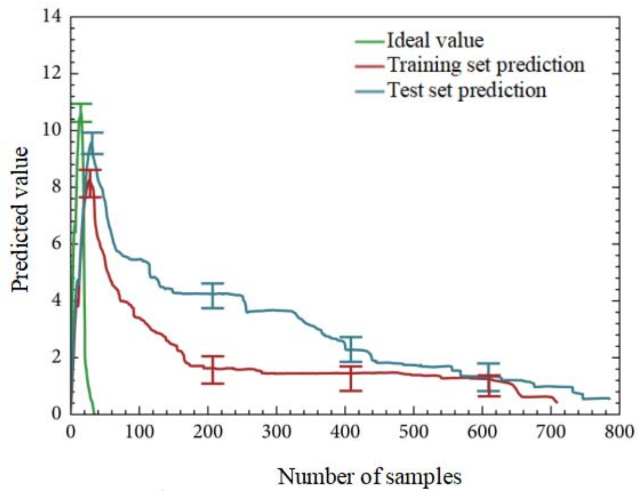

Figure 1 The predicted DTF-LSTM value is compared with the ideal value

The above samples come from different in-wing engines of the same model. These engines are all in the same stage of performance degradation, so as to avoid the influence of different performance degradation rates on the fusion effect in different stages of aero-engines. Generally speaking, when the EGTM falls to 0℃, the engine must be removed and sent for repair. In order to ensure that the EGTM does not exceed the standard, the EGTM when the engine 1 is removed is set to 20℃. LSTM is characterized by replacing common hidden layer nodes with memory blocks, ensuring that the storage of information spans any delay and returns the error signal to the time point long ago, so that the network can learn to "forget" and stay away from saturation. The ideal value of bearing degradation value is a straight line from 0 to 1, while the predicted value fluctuates up and down around the ideal value. The time point when the equipment starts to degrade can be quickly captured; With the increase of time, the predicted value converges to the real value, and the oscillation weakens. Data pretreatment is carried out respectively according to working conditions, and then the data are input into a regression model to build a device health value curve. According to the degradation starting point, power function is used to describe the change of engine degradation process with sampling time. Set to 1 before the degradation starting point and set to 0 for complete failure. In order to facilitate comparison, the absolute error and relative error of the predicted value and the ideal value are calculated to directly reflect the deviation degree between the predicted degradation value and the ideal value [8]. As shown in Table 1.

Table 1 Error comparison of DTF-LSTM prediction values

Data type	Mean absolute error	Average relative error/%
All data	0.0385	7.1541
Training set	0.0451	9.3840
Test set	0.0644	5.2854

There are hundreds of parameters recorded in the flight data recording system. The key to establish an accurate model is to select some parameters that are relevant to the target object. It is necessary to adopt correct analysis methods. Bayesian methods are mostly used in the world to improve the utilization efficiency of small sample data. EGTM parameter has the largest fluctuation range, which can be regarded as the most sensitive parameter to characterize the performance degradation. This can also explain why EGT single parameter is often selected for engine performance degradation control in engineering. However, the extrapolation prediction is actually beyond the effective range of empirical induction. Without the support of domain knowledge, higher-order polynomial fitting is more risky than linear fitting. Therefore, the number of neurons in LSTM input layer in DTF-LSTM model is equal to the number of EGTM current or historical data predicted by input DTF-LSTM model, and the number of neurons in LSTM output layer is equal to the number of EGTM future values predicted by DTF-LSTM model. In order to directly reflect the remaining service life of the tested bearing, the degradation value of the aero-engine output from the long-term and short-term memory network is directly mapped to the remaining service life of the corresponding group number, and the predicted curve of the remaining service life of the aero-engine is obtained by fitting each predicted point with a second-order polynomial as shown in fig. 2.

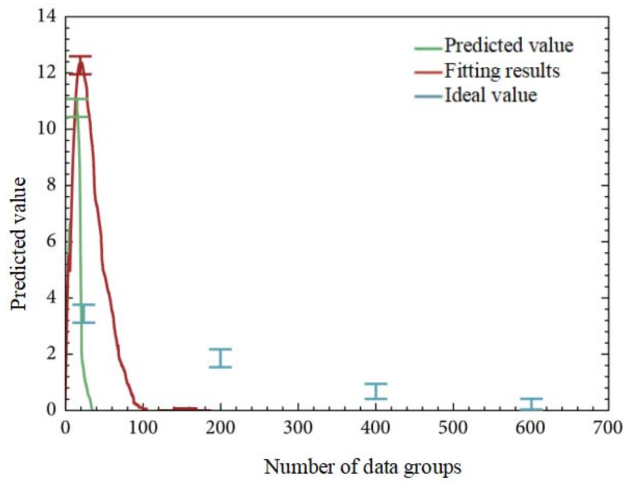

Figure 2 Remaining service life of aeroengine

The algorithm can well predict the initial value of residual life. When the equipment degrades, it can be predicted quickly. During the degradation process, the residual life can be predicted more accurately, but it tends to be overestimated. With the increase of time, the predicted value converges to the real value, the prediction accuracy increases and the reliability increases. This shows that the method of using long-term and short-term memory network to predict and using second-order polynomial fitting to obtain the remaining service life of aeroengine is effective.

IV.Summary

In this paper, the improved differential time domain feature and LSTM are introduced to predict the residual life of aeroengine. LSTM is used to automatically extract the local abstract features of sensor data to avoid manual feature extraction, thus improving the portability of the algorithm. Thanks to the introduction of differential time domain features, the correlation between sensor data and pilot operation modes is established, and the depth mining of sensor data is realized. Taking EGTM data as the experimental object, DTF-LSTM model is constructed by means of feature selection and parameter optimization. The results show that, for the whole data, DTF-LSTM model can reflect the change rule of EGTM more accurately, with faster convergence speed and smaller steady-state error. Through studying the actual failure problems, the role of the model is further exerted, and through selecting scientific and reasonable model technology and learning relevant data, the interaction mechanism of various failure modes is analyzed, so as to improve the reliability and accuracy of aviation engine life prediction.

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