Prediction of Remaining Useful Life of Turbofan Engine Based on Optimized Model

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***Abstract*—To realize the prognostics and health management(PHM) of the mechanical system, it is the key to accurately predict the remaining useful life(RUL) of the equipment. The network captured features at different time steps will contribute to the final RUL prediction to varying degrees. Therefore, a deep learning network based on the attention mechanism is proposed. Firstly, the raw sensor data is passed to the Bi-LSTM network to capture the long-term dependence of features. Secondly, the Bi-LSTM output features are passed to the attention mechanism for features weighting, thereby giving greater weight to important features. Finally, the weighted features are input into the fully connected network to further predict the RUL of the turbofan engine. Using the data set C-MAPSS to explore the feasibility of this method. The results show that this method is more accurate than other RUL prediction methods.**

Keywords—prognostics and health management, remaining useful life, turbofan engine, attention mechanism

I. Introduction

Prognostics and health management (PHM) systems can usually provide some help for equipment failure prediction. Remaining useful life (RUL) prediction is the basis for PHM, and very important for maintaining the normal operation of the equipment. Through accurate RUL prediction, a maintenance plan can be designed in advance to maintain the normal working condition of the equipment and prevent sudden failures from causing huge economic losses. RUL prediction methods usually include: model-based methods[1], data-driven methods[2] and hybrid methods[3]. Model-based methods usually require the establishment of mathematical models to simulate the operation of the entire equipment. However, as the mechanical system becomes more and more complex, it becomes impractical to establish an accurate mathematical model. Hybrid methods want to simultaneously use the advantages of model-based methods and data-driven methods, and there are still greater challenges in preventing shortcomings. Therefore, data-driven prediction of RUL is the current mainstream method.

Time series problems usually use data-driven methods to predict RUL, which can help predict the health of equipment. At present, there are many machine learning methods in RUL prediction methods. Ompusunggu et al.[4]proposed a method to use Kalman filter (KF) to predict the RUL of automatic transmission clutches. Javed et al.[5]used an extreme learning machine (ELM) to predict the RUL of lithium batteries. RUL predictions often use deep learning networks, such as long short-term memory (LSTM) networks and bi-directional long short-term memory (Bi-LSTM) networks. The original recurrent neural network (RNN), due to the disappearance of gradients, makes RNN not widely used. The proposed improved network LSTM effectively overcomes this shortcoming. Wu et al.[6] used vanilla LSTM to predict engine RUL. Al-Dulaimi et al.[7] use one-dimensional convolutional neural network (1D-CNN) combined with recurrent neural network (LSTM and Bi-LSTM) to predict the RUL of turbofan engines. What these networks have in common is that only the learned features in the last step are used to predict RUL, but perhaps the features learned in other time steps will also have varying degrees of impact on the final RUL prediction. Therefore, it is particularly important to assign different weights to various learning features at different time steps.

In order to achieve feature weighting, this paper proposes an attention-based deep learning method. First, the Bi-LSTM network learns original features. Secondly, the attention mechanism is used to produce output features for Bi-LSTM, giving more attention to important output features, providing a good foundation for further learning of the fully connected network, and helping the network accurately predict the RUL of the turbofan engine.

II. Methods

Fig. 1 details the entire network framework of this method. Want to make full use of input data and capture the bi-directional long short-term dependence of the input features, this article uses Bi-LSTM network for feature learning. Bi-LSTM is created on the basis of traditional LSTM, which has been proved to have more advantages than LSTM in many fields. Sensor measurement data is transferred to Bi-LSTM network for initial feature learning. The continuous features of network learning are used as the input data of the attention mechanism. Through the attention mechanism, more weight can be assigned to important features output at different time steps. Highlighting key features provides a good foundation for further RUL prediction and help the network predict RUL more accurately.

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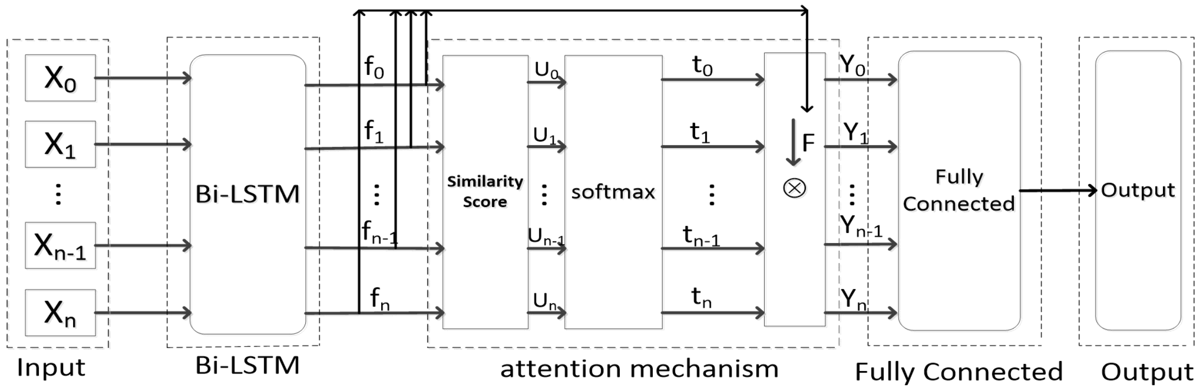

Fig. 1. Model structure

A. Bi-LSTM

Bi-LSTM includes two layers of LSTM and the information transfer direction of the two layers of LSTM is opposite, and the final output sequence is a combination of the results of the two layers. Fig. 2 shows the specific network structure of Bi-LSTM. At time t, the Bi-LSTM model calculates two values in the forward and reverse directions, the final output is the combination of the two values.(1)-(6) shows forward propagation:

$$\overrightarrow{a}_t = \tanh(\overrightarrow{W}_a \overrightarrow{x}_t + \overrightarrow{U}_a \overrightarrow{h}_{t-1} + \overrightarrow{b}_a) \tag{1}$$

$$\overrightarrow{f}_t = \sigma(\overrightarrow{W}_f \overrightarrow{x}_t + \overrightarrow{U}_f \overrightarrow{h}_{t-1} + \overrightarrow{b}_f) \tag{2}$$

$$\overrightarrow{i}_t = \sigma(\overrightarrow{W}_i \overrightarrow{x}_t + \overrightarrow{U}_i \overrightarrow{h}_{t-1} + \overrightarrow{b}_i) \tag{3}$$

$$\overrightarrow{o}_t = \sigma(\overrightarrow{W}_o \overrightarrow{x}_t + \overrightarrow{U}_o \overrightarrow{h}_{t-1} + \overrightarrow{b}_o) \tag{4}$$

$$\overrightarrow{c}_t = \overrightarrow{f}_t \odot \overrightarrow{c}_{t-1} + \overrightarrow{i}_t \odot \overrightarrow{a}_t \tag{5}$$

$$\overrightarrow{h}_t = \overrightarrow{o}_t \odot \tanh(\overrightarrow{c}_t) \tag{6}$$

The formula for back propagation is the same as the formula for forward propagation, so it is no longer listed in detail. Where i_t, o_t, f_t respectively represent the result obtained by the input gate, the result obtained by the output gate and the result obtained by the forget gate of the forward propagation process at time t.

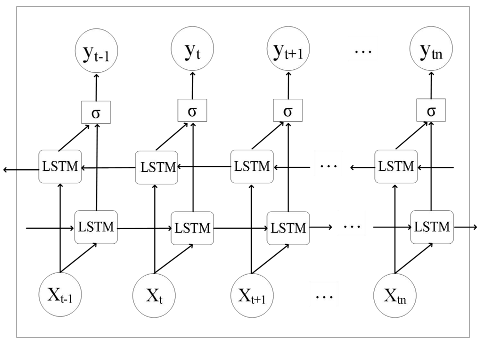

Fig. 2. Bi-LSTM Structure

B. Attention Mechanism

Introducing an attention mechanism to assign greater weights to important features learned at different time steps to achieve a more accurate prediction of the RUL of turbofan engines. Assume that the features learned by the Bi-LSTM network are expressed as: $F= \{f_1, f_2, ..., f_d\}^T$, T represents the transpose operation. Using attention mechanism, the feature weight of the input f_i at the ith time step is expressed as:

$$U_i = \phi(W^T f_i + b) \tag{7}$$

Where W represents the initial weight, b represents the bias, U_i represents the corresponding score obtained, which is normalized using the softmax function. The expression is as follows:

$$t_i = softmax(U_i) = \frac{\exp(U_i)}{\sum_i \exp(U_i)} \tag{8}$$

The features output by attention are expressed as:

$$Y = F \otimes B \tag{9}$$

Where $B= \{t_1, t_2, ..., t_d\}$, $\otimes$ represents multiplication.

III. Experimental Results and Discussion

A. Description of Dataset

This article uses the C-MAPSS data set to evaluate the method. The C-MAPSS data set has four subsets of FD001-FD004. Each data set has a training data set and a test data set. The training model uses the training set, and the model evaluation uses the test set. The RUL file records the real RUL in the test set and is used to evaluate the accuracy of the prediction RUL method. Each data set has 26 columns, including one column of engine numbers, one column of cycle numbers, three columns of operating conditions, and 21 columns of sensor measurement data. The data set information is in Table I.

TABLE I. Datasets description

Dataset	FD001	FD002	FD003	FD004
Operational modes	1	6	1	6
Fault modes	1	1	2	2
Training engines	100	260	100	249
Testing engines	100	259	100	248

B. Sliding Window Processing

After processing the original data through a sliding time window, the input data of the Bi-LSTM network is generated. The input data processed by the time window can be expressed as $N= [X_1, X_2, ..., X_n]$. Since the correlation between different data points is very important for time series problems, the time window captures these correlations, and the correlations of multiple data points are encapsulated in a sliding window. And use the sliding window to process the original data, which can realize the expansion of the data. In order to facilitate the display, in Fig. 3 the length of the sliding window is set to 2, and the sliding stride is set to 1.

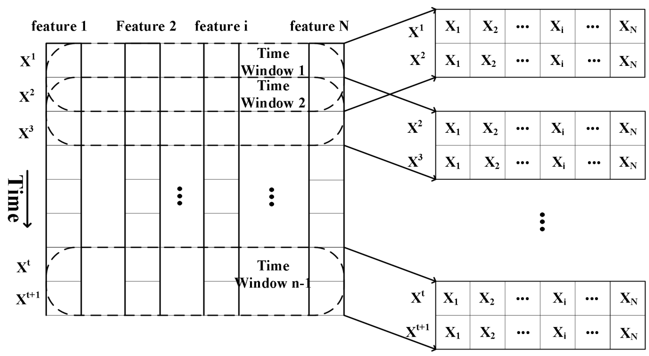

Fig. 3. Time Window processing

C. Performance Metrics

In this article, to evaluate the RUL prediction performance of this method, we use the root mean square error (RMSE) and scoring function. Use RMSE to show the gap between the actual RUL and the model predicted RUL. The formula is as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(d)^2} \quad (10)$$

Where $d=RUL_{prediction} - RUL_{actual}$, $RUL_{prediction}$ represents the RUL value estimated by the model, RUL_{actual} represents the real RUL value, and n is the number of test data.

Another widely used evaluation index is the scoring function, which can evaluate the estimated performance of the model RUL. The method should be able to predict RUL in advance, so that maintenance can be carried out before failure occurs. The formula is as follows:

$$Score = \begin{cases} \sum_{i=1}^{n} e^{-\left(\frac{d}{13}\right)} - 1, d < 0 \\ \sum_{i=1}^{n} e^{\frac{d}{10}} - 1, d \geq 0 \end{cases} \quad (11)$$

D. Technology Application

The raw data is processed through the sliding window to generate the input data of the network. Due to the huge amount of raw data, small batches are selected for model training. When training the model, the training data set is split into 20% validation set and 80% training set. In order to avoid over-fitting, the dropout technique is applied to the model, and Adam is used as the optimization function.

E. Comparisons with Other Approaches

We use the C-MAPSS data set to verify the accuracy of the method. The method in this article is compared with some other RUL prediction methods, and the experiment proves the superiority of our method. Because there is a certain degree of randomness in the prediction performance of the model, we have conducted many experiments to obtain the average results of RMSE and Score. As shown in Tables II and Tables III. Compared with other turbofan engine RUL prediction methods, proposed method has achieved good results on the two data sets FD002 and FD004.

TABLE II. RMSE OF PUBLIC APPROACHES ON C-MAPSS

Methods	FD001	FD002	FD003	FD004
RF[8]	17.91	29.59	20.27	31.12
GB[8]	15.67	29.09	16.84	29.01
LSTM[9]	16.14	24.49	16.18	28.17
BiLSTM[10]	13.65	23.18	12.74	24.86
LSTMBS[11]	14.89	26.86	15.11	27.11
RBM+LSTM[12]	12.56	22.73	**12.1**	22.66
AGCNN[13]	**12.42**	**19.43**	13.39	**21.5**
Our（mean）	13.78	**15.94**	14.36	**16.96**

TABLE III. SCORE OF PUBLIC APPROACHES ON C-MAPSS

Methods	FD001	FD002	FD003	FD004
RF[8]	479.95	70456.86	711.13	46567.63
GB[8]	474.01	87280.06	576.72	17817.92
LSTM[9]	338	4450	852	5550
BiLSTM[10]	295	4130	317	5430
LSTMBS[11]	481.1	7982	493.4	5200
RBM+LSTM[12]	**231**	3366	251	2840
AGCNN[13]	225.51	**1492**	**227.09**	**3392**
Our（mean）	255.07	**1285.67**	438.68	**1651.97**

Selecting the results of an experiment, the predicted RUL of the four data sets are shown in Fig. 4-Fig. 7. For these four data sets, the predicted RUL is very close to the real RUL, which shows the feasibility of the proposed method. Because the FD001 and FD003 data sets have a single operating condition and a small number of engines, the prediction results of FD001 and FD003 are better than FD002 and FD004.

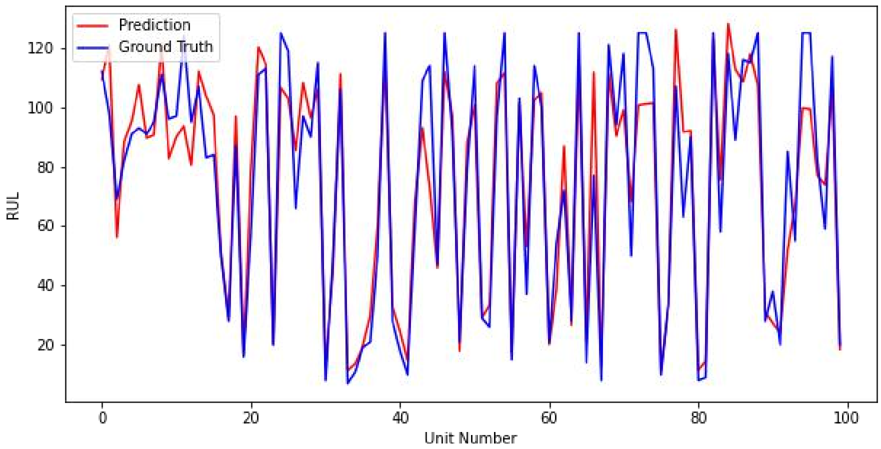

Fig. 4. FD001 RUL forecast results

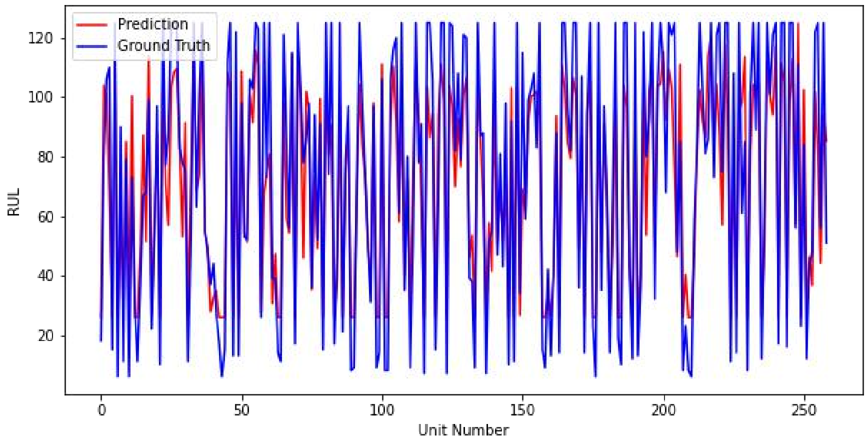

Fig. 5. FD002 RUL forecast results

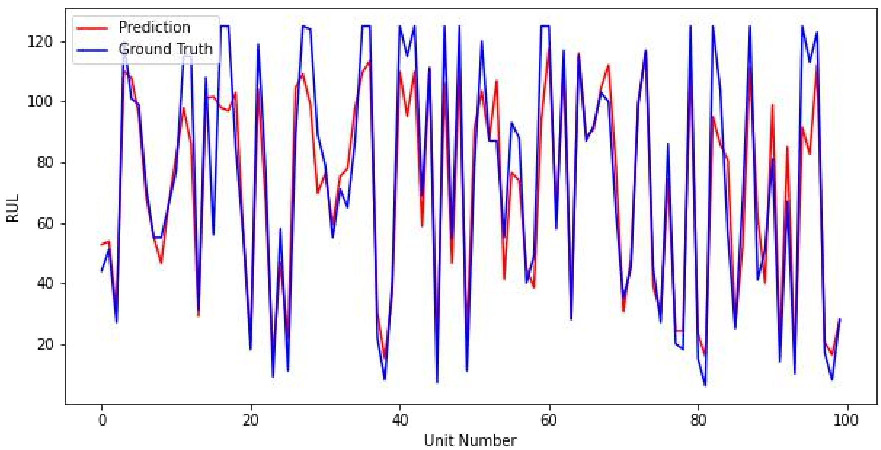

Fig. 6. FD003 RUL forecast results

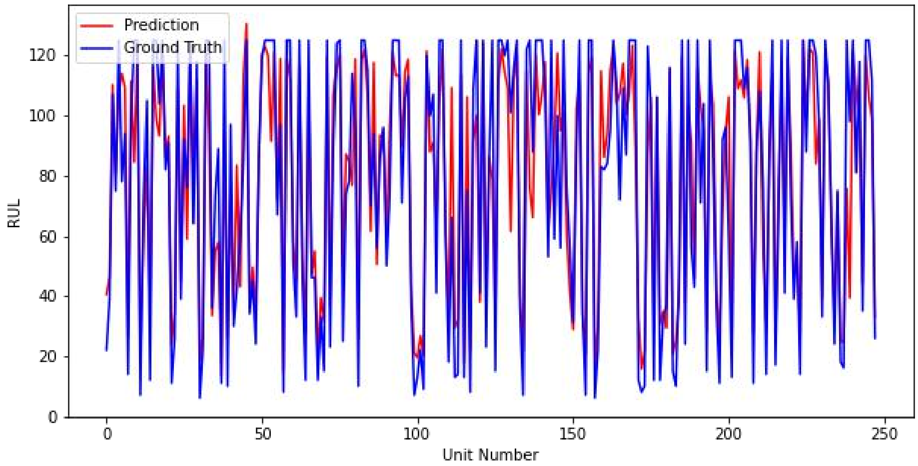

Fig. 7. FD004 RUL forecast results

IV. Conclusion

This paper proposes an attention-based deep learning model to predict the RUL of turbofan engines. Sensors data are input into Bi-LSTM network for preliminary feature learning. The feature input attention mechanism of Bi-LSTM network learning. The attention mechanism can give more weight to important features at different time steps, laying a solid foundation for accurately predicting turbofan engine RUL. Compared with the latest RUL prediction method, the obtained results show that this method has better prediction performance. The proposed method has achieved good results on complex data sets, but the prediction results of FD001 and FD003 still need to be further optimized.

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