Predicting Remaining Useful Life of Industrial Equipment Based on Multivariable Monitoring Data Analysis

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***Abstract*—Modern industrial equipment plays a vital role in the operation of large industrial systems. Accurate prediction of its remaining useful life will greatly reduce the possibility of unsafe accidents. The internal structure of modern industrial equipment is very complex, and a variety of state monitoring data affect the remaining useful life of the equipment, and the mutual influence between different monitoring data has greatly increased the difficulty of remaining useful life prediction. In this paper, the long short-term memory network in deep learning is used to solve this problem. The long short-term memory network has many advantages in time series prediction. The remaining useful life prediction model of industrial equipment based on long short-term memory network and multivariable monitoring data is established, and aiming at the characteristics of multivariable monitoring data, Mini-batch Gradient Descent algorithm (MBGD) is adopted to train the network. Finally, the engine monitoring data set provided by the NASA prediction center is used to verify the algorithm. The data set is divided into training set and test set, the training set is put into the long short-term memory network to get the prediction model, and then the remaining useful life prediction is carried out by the test set. The prediction accuracy and generalization ability of the algorithm are verified by predicting the remaining useful life of three different turbofan engines.**

Keywords-remaining useful life prediction; long short-term memory network; industrial equipment; multivariable

I. INTRODUCTION

Prognostics and Health Management (PHM) refers to the use of sensors to acquire the data information of the system, using various intelligent models and algorithms to evaluate the health status of the system itself, predicting before the system failure occurs, and providing a series of information together with the available resource information. The maintenance safeguards are recommended to achieve the system's conditional maintenance [1]. It is a supportive discipline consisting of methods and techniques for assessing system reliability under real life conditions to detect initial failures and predict failure development [2].

Modern industrial equipment plays a vital role in the operation of large industrial systems. Often its working state directly or indirectly affects the entire operating state of the equipment, so the prediction of its remaining useful life is of great significance [3]. Modern industrial equipment generally has a complex internal structure, and the amount of condition monitoring that determines its remaining useful life is not single, but it is determined by a combination of multiple state monitoring quantities. So combining many of the state monitoring quantities into consideration will result in more accurate predictions. For the remaining useful life prediction of a variety of monitoring data, domestic and foreign scholars have done a lot of research in various application fields. Wei et al. [4] recursively identified the degradation process by using distributed fusion filtering based on multi-sensor observation for multi-sensor dynamic systems, and predicted the distribution of remaining useful life by parameter update. Wang et al. [5] proposed a remaining useful life prediction method based on multi-parameter correlation degradation under random environmental stress shock, and used a variety of stochastic process models to fit the degradation data of various performance parameters, and set up the storage life prediction model for the competition between the degradation failure and the sudden failure. Liang et al. [6] proposed a remaining useful life prediction method based on multi-parameter similarity information fusion. Shen et al. [7] proposed a remaining useful life method based on relative features and multivariate support vector machines. The results show that accurate prediction results can be obtained by using as much effective information as possible in small sample conditions. He et al. [8] proposed a bearing remaining useful life prediction method based on principal component analysis and multivariate extreme learning machine, which obtained higher prediction accuracy and stability.

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The above method mostly adopts the model-based method when solving the problem of remaining useful life of multivariable and multi-parameters, but the problem of multivariate will be inaccurate in the modeling process, the model is complex, and the parameters are difficult to identify. These methods have some limitations. In recent years, with the development of neural networks, the recurrent neural network (RNN) has the ability of "memory", and many scholars have applied it to the modeling and prediction of sequence information, and achieved remarkable results [9]. However, the traditional RNN has the problem of gradient disappearance in the process of information feedback. Hochreiter and Schmidhuber proposed the strategy of long short-term memory (LSTM) network to solve the problem that RNN can't model long-span sequences [10,11]. Combined with historical status, current memory and current input, gate control units are introduced to deal with long sequence dependence problems.

In this paper, the remaining useful life prediction model of industrial equipment based on long short-term memory network and multivariable monitoring data is established, and a turbofan engine data set is used to verify the effectiveness of the prediction model in solving the multivariable remaining useful life prediction.

II. THE BASIC STRUCTURE OF LONG SHORT-TERM MEMORY NETWORK

The long short-term memory network is an improved algorithm of the recurrent neural network (RNN). The network structure of the RNN is shown in Figure 1. Because the traditional RNN has a gradient disappearance problem in the information feedback process, in order to solve this problem, Hochreiter and Schmidhuber proposed a long short-term memory (LSTM) network strategy to solve the problem that RNN cannot model large time-span sequences [10,11], combined with the historical state, current memory and current input to introduce the gating unit to handle the long sequence dependency problem.

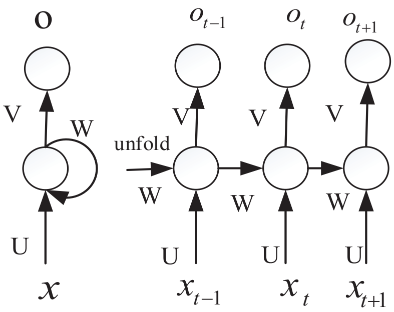

Figure 1. Basic RNN network structure

The long short-term memory network shows great advantages in the long-span sequence prediction problem. Therefore, based on the long short-term memory network, the multi-variable engine remaining useful life prediction model is established to solve the multi-variable engine remaining useful life prediction problem. Firstly, the basic structure of the long short-term memory network is introduce briefly.

The long short-term memory network structure is shown in Figure 2. $x^{(t)}$ is the input layer at time t, and $h^{(t-1)}$ is the hidden layer at time $t-1$. A "gate" is a prominent feature of the long short-term memory network that selectively determines what information should be passed. There are three gates in the network structure of the long short-term memory, namely input gate, forget gate and output gate. They will be introduced separately below.

Forget Gate: The role of the forget gate is to decide what information will be discarded. Its inputs are $x^{(t)}$ and $h^{(t-1)}$, use sigmoid function as the activation function, so a value between 0 and 1 is output for each state value in the internal state. 1 means that the state value is completely reserved, and 0 means that the value is completely discarded. The forget gate calculation formula is as follows:

$$f^{(t)} = \sigma(W_f x^{(t)} + W_f h^{(t-1)} + b_f) \quad (1)$$

Input Gate: The purpose of the input gate is to determine what new information will be stored in the internal state. Firstly, by using the sigmoid function, $i^{(t)}$ can be got. It can determine which values to update. Then, by using the tanh function, $g^{(t)}$ can be got. The formula for calculating the two outputs is as follows:

$$i^{(t)} = \sigma(W_i x^{(t)} + W_i h^{(t-1)} + b_i) \quad (2)$$

$$g^{(t)} = \tanh(W_g x^{(t)} + W_g h^{(t-1)} + b_g) \quad (3)$$

Update the previous internal state $s^{(t-1)}$ to the current state $s^{(t)}$ in combination with equations (1)-(3):

$$s^{(t)} = g_t \times i^{(t)} + s^{(t-1)} \times f^{(t)} \quad (4)$$

Output Gate: The purpose of the output gate is to determine what information to output. After the internal state is passed through the tanh function, it is multiplied by the output of the sigmoid function to get the residual state value. Calculated as follows:

$$o^{(t)} = \sigma(W_o x^{(t)} + W_o h^{(t-1)} + b_o) \quad (5)$$

$$h^{(t)} = \tanh(s^{(t)}) \times o^{(t)} \quad (6)$$

Where W is the weight matrix of the gate and b is the bias term of the gate.

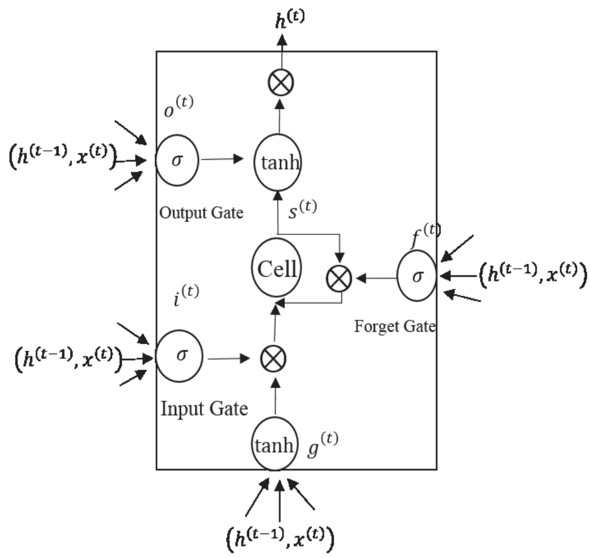

Figure 2. Long short-term memory network structure

III. REMAINING USEFUL LIFE PREDICTION OF MULTIVARIABLE INDUSTRIAL EQUIPMENT BASED ON LONG SHORT-TERM MEMORY NETWORK

A. Remaining useful life prediction model of multivariable coupling industrial equipment based on long short-term memory network

The state characteristics of the industrial equipment monitored during the operation can be considered as the time series, and a certain device has n state features, and the parameters features of the t time are monitored. That is, the input vector is as follows:

$$X = \{x_1^t, x_2^t, ..., x_n^t\}$$

Where, the subscript indicates the type of status detected, and the superscript indicates the time.

The output vector $Y = \{y^t\}$ and y^t represents the remaining useful life at time t. So the overall flow of multivariable remaining useful life prediction algorithm based on long short-term network is shown in Figure 3.

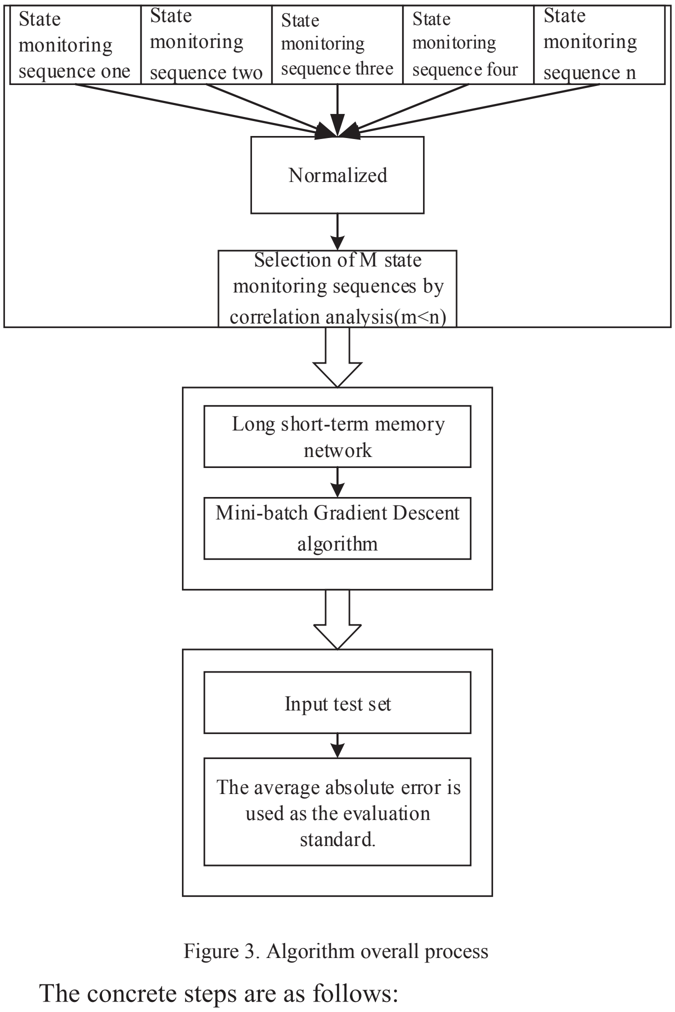

Figure 3. Algorithm overall process

The concrete steps are as follows:

Step1: Get monitoring data. It includes state monitoring values and corresponding remaining useful life span, and data sets are divided into training sets and test sets.

Step2: To ensure that different state monitoring values have the same impact on model training. The data set is normalized using the Z-Score normalization method.

Step3: In order to reduce the complexity of the network, the correlation between different state monitoring sequences and remaining useful life is analyzed, and the state monitoring sequence with high correlation is selected for model training.

Step4: According to the characteristics of the network input vector, the training algorithm of the long short-term network is used to train the training sets to obtain the predictive model.

Step5: The test set is entered into the predictive model to obtain a predicted value of the remaining useful life.

Step6: Prediction effect evaluation. The mean absolute error (MAE)and root mean square error (RMSE) is used to evaluate the effect.

B. Long short-term memory network training algorithm

Generally, the training algorithm of the long short-term memory network is a Backpropagation Algorithm (BPTT). The algorithm has the following three main steps:

Step1: Calculate the output value of each neuron in the forward direction. In the long short-term memory network, the value of the five vectors $f^{(t)}, i^{(t)}, s^{(t)}, o^{(t)}, h^{(t)}$ can be got.

Step2: Calculate the error term of each neuron in reverse, which is the partial derivative of the weighted input of the error function to the neuron. In long and short memory networks, the backpropagation of the error term consists of two directions, one is the back propagation along time, and the other is to propagate the error term up one level.

Step3: The gradient of each weight is calculated based on the corresponding error term.

According to the characteristics of the input vector in the engine remaining useful life prediction model based on the long short-term memory network established in this paper, the number of nodes in the input layer is m, and the number of nodes in the input layer is one. Therefore, the method adopted for the training of long short-term memory networks is Mini-batch Gradient Descent algorithm (MBGD). The Mini-batch Gradient Descent algorithm uses a portion of the samples to update each parameter as it is updated, and it performs a gradient update for a minimum batch of b training samples. Compared to batch gradient descent algorithm (BGD) and stochastic gradient descent algorithm (SGD), the Mini-batch Gradient Descent algorithm uses a highly optimized matrix optimization to simultaneously calculate the gradient of b samples, which is very efficient for deep learning. This calculation reduces the variance of the gradient update, which results in more stable convergence [12].

IV. EXPERIMENT AND RESULT ANALYSIS

A. Data description and preprocessing

In this paper, the dataset is a set of data sets from normal operation to failure of turbofan engine provided by NASA prediction center. The data set consists of 4 sets of data sets in different operating states and failure modes, of which 21 sensors and 3 input parameters are used to record the entire degradation process of the engine. These engines are in normal condition at first and then occur at a certain time and appear apparent performance degradation[13], and the degradation continues until the system fails.

In order to verify the generalization ability of the method, the monitoring data of the second engine in the first group of operating states, the monitoring data of the eleventh engine in the second group of operating states, the fourth in the third group of operating states and the monitoring data of the second engine in the fourth group of operating states are selected for experimental verification respectively.

Firstly, the data is normalized. The mean and standard deviation of the raw data are calculated to standardize the data. Then, the similarity analysis is performed on the monitoring data and the remaining useful life. That is, the Euclidean distance between the monitoring data value and the remaining life is calculated separately. The monitoring data of the sensor with high similarity to the remaining useful life is selected as the input of the network for training.

B. Experimental result

In this paper, the monitoring data of the second engine in the first group of operating conditions (No. 1), the monitoring data of the eleventh engine in the second group of operating conditions (No. 2), and the fourth in the third group of operating states (No. 3) are experimentally verified. Figure 4 shows the result of the Euclidean distance between the No. 1 engine monitoring sequence and the remaining useful life sequence.

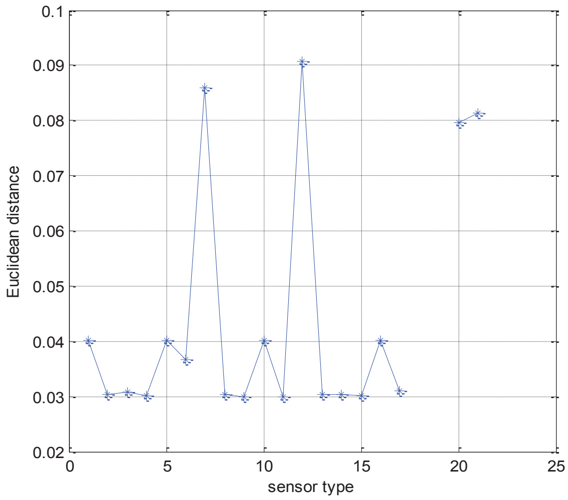

Figure 4. No. 1 engine Euclidean distance result

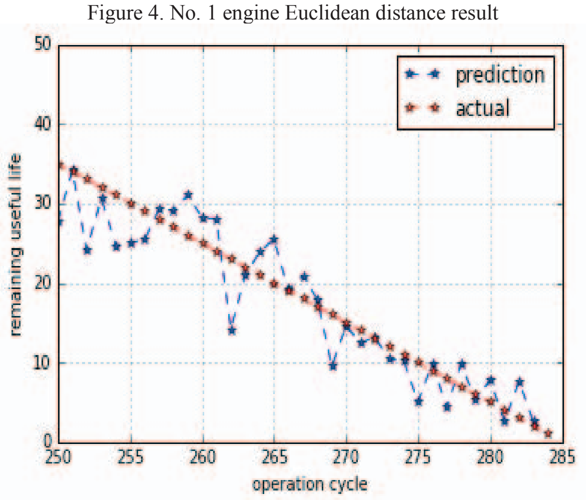

Figure 5. Remaining useful life prediction result of the No. 1 engine

It can be seen from Fig. 4 that among the 21 sensor monitoring data, the Euclidean distance of the monitoring data of 10 sensors and the remaining useful life are approximately equal to 0.03. The 10 sensor monitoring sequences are selected as the input of the network for training. Figure 5 shows the remaining useful life prediction result of the No. 1 engine.

Figure 6 shows the result of the Euclidean distance between the No. 2 engine monitoring sequence and the remaining useful life sequence.

It can be seen from Fig. 6 that among the 21 sensor monitoring data, the Euclidean distance of the monitoring data of 7 sensors and the remaining useful life are less than 0.04. The seven sensor monitoring sequences are selected as the input of the network for training. Figure 7 shows the remaining useful life prediction result of the No. 2 engine.

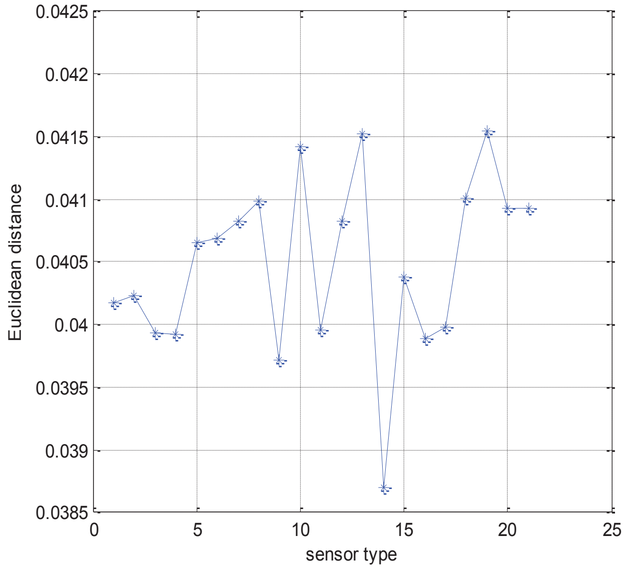

Figure 6. No.2 engine Euclidean distance result

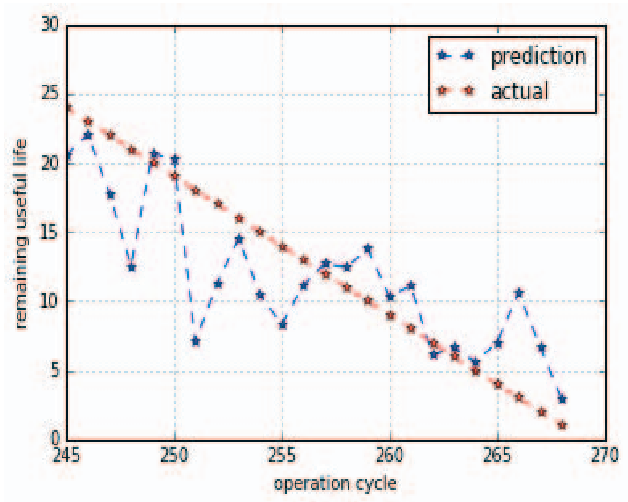

Figure 7. Remaining useful life prediction result of the No.2 engine

Figure 8 shows the result of the Euclidean distance between the No. 3 engine monitoring sequence and the remaining useful life sequence.

It can be seen from Fig. 8 that among the 21 sensor monitoring data, the Euclidean distance of the monitoring data of 8 sensors and the remaining useful life are approximately equal to 0.03. The eight sensor monitoring sequences are selected as the input of the network for training. Figure 9 shows the remaining useful life prediction result of Engine No. 3.

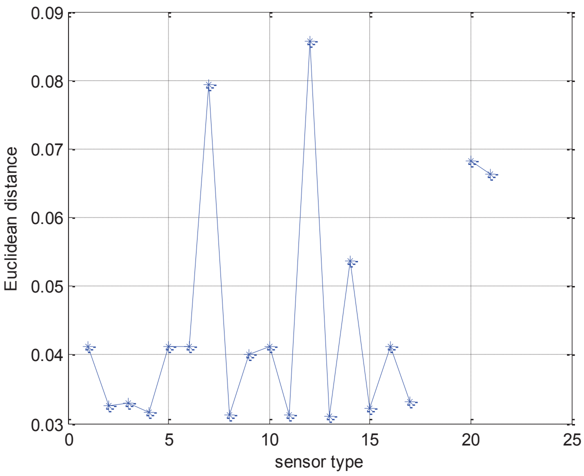

Figure 8. No. 3 engine Euclidean distance result

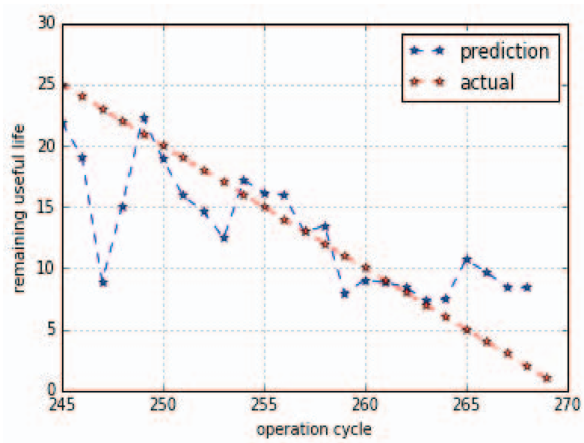

Figure 9. Remaining useful life prediction result of the No.3 engine

Where, the abscissa indicates the operating period of the turbofan engine, and the ordinate indicates the remaining useful life. In order to display the prediction effect more intuitively, the mean absolute error and root mean square error are used to evaluate the prediction effect. Table 1 is the evaluation of remaining useful life prediction results of three engines.

TABLE I. EVALUATION OF REMAINING USEFUL LIFE PREDICTION RESULTS OF THREE ENGINES

Engine number	No.1	No.2	No.3
Mean absolute error	3.01	2.27	3.80
Root mean square error	4.28	3.85	4.49

It can be seen from the prediction results that the remaining useful life prediction model of multivariable engine based on long short-term memory network can predict the remaining useful life of the engine, and the prediction accuracy is high. It has achieved good results by predicting the remaining useful life of the three engines. The generalization ability of the algorithm is proved.

V. CONCLUSION

Remaining useful life prediction is the core issue of prognostics and health management (PHM). Remaining useful life prediction can provide the possible failure time of equipment in advance. In particular, modern industrial equipment plays a vital role in the operation of large industrial systems, and it is more important to predict the remaining useful life of the industrial equipment.

In this paper, remaining useful life prediction problem for industrial equipment based on multivariate monitoring data, the remaining useful life prediction model of industrial equipment based on long short-term memory network and multivariable monitoring data is established, and the Mini-batch Gradient Descent algorithm(MBGD) is adopted in the training process of the prediction model, which ensures the fast finding of the global optimal solution. Then, the engine monitoring data set provided by the NASA prediction center is used to verify the correctness of the prediction model. The data set is divided into training set and test set, the training set is put into the long short-term memory network to get the prediction model, and then the remaining useful life prediction is carried out by the test set. The remaining useful life prediction results of three different turbofan engines show that the prediction model has high prediction accuracy and generalization ability.

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