Construction Method of Turbine Engine Health Indicator Based on Deep Learning

Yongcheng Gao[1], Jun Zhou[2], Kankan Wu[2], Guangquan Zhao[1]*, Cong Hu[3]
[1]School of Electronics and Information Engineering, Harbin Institute of Technology, Harbin 150080, China
[2]Shanghai Institute of Satellite Engineering, Shanghai 200240, China
[3]Guangxi key Laboratory of Automatic Detecting Technology and Instruments, Guilin University of Electronic Technology Guilin 541004, China
Phone: +8645186413532, Fax: +8645186402953, Email: hit53zhao@hit.edu.cn

***Abstract*—Traditional turbine engine health indicator (HI) construction methods generally require manual feature extraction, feature selection and even feature fusion, besides, training labels need to be designed in advance, which make the whole procedure time consuming and not universal. Therefore, this paper proposes a novel unsupervised construction method of turbine engine health indicator based on stacked denoising autoencoders (SDAE). In this method, the deep structure of autoencoders adaptively extracts features of raw turbine engine monitoring signals in an unsupervised way to obtain its health indicator. Experimental results on CMAPSS engine dataset show that the HI curves constructed by the proposed method can well reflect the degradation process of turbine engine during the whole life cycle, and have better correlation and monotonicity compared to the traditional HI construction methods. Moreover, the proposed method does not need to rely on complex signal processing measures, the whole process is carried out in an unsupervised manner with a certain degree of versatility.**

Keywords-health indicator; deep learning; stacked denoising autoencoders; unsupervised learning;

I. INTRODUCTION

Turbine engines are one of the most common and important aircraft components. According to NASA, the engine accounts for 1/3 of all mechanical failures in civil aircraft, and airlines around the world suffer from $31 billion in maintenance costs each year [1]. Therefore, it is of great significance to ensure its reliable operation state for the stable operation of aircraft and prevent heavy losses.

Due to the complex operating conditions of the turbine engine, it is difficult to establish an accurate physical model for its degradation process. Benefiting from the development of sensor technology and storage technology, the data-driven approach has gradually become the mainstream approach due to the availability of a large number of turbine engine health monitoring data. According to the characteristics of the health status of the target object reflected by the processing data, that is, the health indicator (HI) curve that characterizes the degradation behavior and life of the target system, the data-driven fault prediction method can be divided into two categories: direct prediction and indirect prediction. Since the direct prediction method is to directly use the original data as the HI of the measured object, the HI curve is usually poorly monotonous, which is not conducive to the subsequent turbine engine residual life prediction. Therefore, domestic and foreign scholars have done extensive researches on the indirect HI construction method.

In the indirect HI construction process of the turbine engine, it is often necessary to evaluate the beneficial information contained in each sensor according to certain evaluation indicators, and then select the sensor monitoring information. After that, feature extraction is required, and feature selection is carried out on this basis to remove redundant features, and feature fusion should be continued if necessary. As a key step, feature extraction method mainly includes methods based on traditional signal processing technology and machine learning [2]. For example, Li Y et al. [3] first used the principal component analysis (PCA) to reduce the dimensionality of multi-sensor data, and then obtained the HI curve by weighted Euclidean distance and regression algorithm. Khelif R [4] et al. used the linear regression and curve fitting to obtain the HI curve after screening the sensor information. In addition, there are methods like cluster analysis, wiener process, vector machine model and neural Networks [5-7], etc. Although the traditional data-driven approach has made significant achievements in the modeling of turbine engine degradation states, the following problems still remain: (1) these methods often need to optimize the original sensor information by means of complex sensor information evaluation criteria, and extracting degraded features and selecting features rely on a large number of human participation. The whole process relies on a large number of expert experience and traditional signal processing methods, (2) some of them are trained in a supervised manner, that is, the actual output value corresponding to the input needs to be provided as a label during the training process, and the selection of the label depends on manual participation, which is time-consuming and has no consistent standard, and (3) in order to obtain a comprehensive monotonic HI curve, it is often necessary to use a variety of signal processing methods for specific problems and rely on manual experience to select parameters, which lacks certain versatility.

The remainder of this paper is as follows: Section II specifies the flow of the HI construction method for the turbine engine based on stacked denoising autoencoders (SDAE). Section III uses the public dataset for experiments and

This research was supported by Guangxi Key Laboratory of Automatic Detecting Technology and Instruments (YQ17202).

compares it with two traditional methods. Section IV draws the conclusion and summarizes this paper.

II. UNSUPERVISED HI CONSTRUCTION OF TURBINE ENGINE BASED ON SDAE

It can be seen from Section I that the traditional turbine engine HI construction method has the problems of not having the ability to automatically extract features, more manual participation, and not universal. The existing HI construction method based on deep learning is also faced with problems such as the selection of training labels, dependence on manual participation, and insufficient denoising ability of the algorithm [8]. Therefore, on the basis of summarizing the deep learning model, this section proposes an unsupervised HI construction method for turbine engines based on SDAE.

A. Deep Learning Model Selection

In order to select a suitable deep learning model for HI construction of turbine engine and overcome the problems existing in current methods, the commonly used deep learning methods as well as their advantages and disadvantages are first summarized in Table I.

TABLE I. SUMMARY OF DEEP LEARNING METHODS

Basic model	Common method	Advantage	Short
Multilayer perceptron	Stacked autoencoder	Strong feature extraction capability and ability to denoise	More training parameters
	Deep belief network	Strong feature extraction ability	More training parameters
Convolutional neural network	Deep convolutional neural network	Weight sharing, low input translation invariance is required	Long training time and complex model
	Deep residual network		
Recurrent neural network	Long Short Term Memory Network	Information memory, suitable for modeling sequence content	No feature learning ability

Due to the fact that effective feature extraction is required in the HI construction process of the turbine engine, and the working environment of the engine is complex and often contains a lot of noise, so the model selected should have the ability of denoising. As can be seen from Table I, the stacked autoencoder (SAE) has good feature extraction capability, and its variant SDAE adds noise factor and has good denoising ability. SDAE is a deep learning algorithm proposed by Vincent et al, which is widely used in speech recognition, text translation, sequence prediction, etc [9]. At the same time, SDAE is an unsupervised learning model that avoids the resource consumption caused by manual design labels. More importantly, it can automatically extract important features from the raw signal of the measured object. With the development of fault prediction and health management research, there have been studies to apply SDAE to the PHM field [10]. In view of the above advantages of SDAE, SDAE is used to construct unsupervised health indicator based on the original sensor monitoring information of turbine engines in this paper.

B. Turbine Engine Health Indicator Construction

The overall process of the method is shown in Figure 1. First, multi-dimensional monitoring data acquisition of the turbine engine is performed, and then sensor selection can be completed by direct observation. Data normalization is required before input to SDAE, and then the training set is input to SDAE for model training. The testing set is then input into the trained model to build HI and evaluate the algorithm. SDAE directly obtains the HI curve of the turbine engine by extracting a single eigenvalue in an unsupervised learning manner.

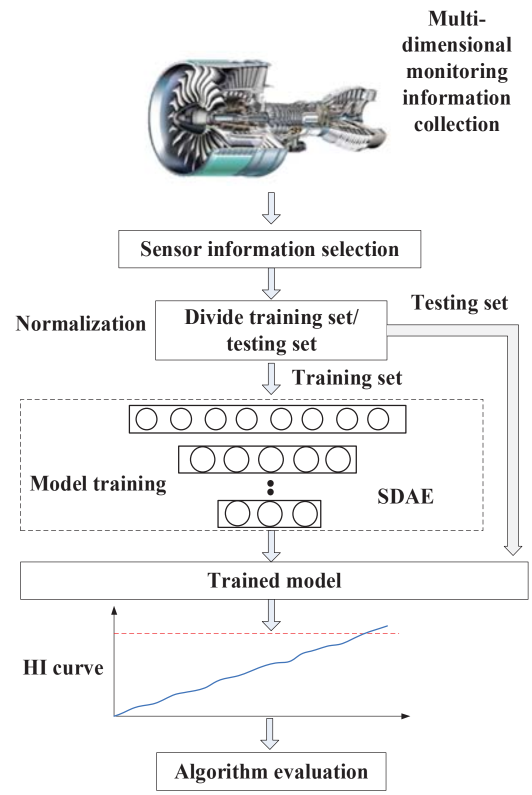


Figure 1. Process of the turbine engine HI construction.

The specific process of turbine engine health indicator construction includes the following steps:

Step 1: Obtain historical degradation data collected by multiple sensors of the engine.

Step 2: Select the monitoring data obtained by multiple sensors, remove the sensor data without changing trend in the monitoring data, and take the monitoring data of the remaining sensors as the input data of SDAE. This paper uses the aircraft engine simulation state public dataset -- CMAPSS [11]. Files named "train_FD001" and "test_FD001" provided by the dataset are used as the training set and testing set for HI construction.

This data is the monitoring data of 21 sensors under a single working condition. According to the data analysis, only the 14-dimensional information in the 21-dimensional sensor information has different degrees of trend (#2, #3, #4, #7, #8, #9, #11, #12, #13, #14, #15, #17, #20, #21), the remaining 7-dimensional monitoring information has no trend change and does not have useful information. Figure 2 to Figure 4 respectively give specific degradation data for sensor #2 with all units having an upward trend, sensor #7 with all units falling, and sensor #14 with inconsistent unit change trends.

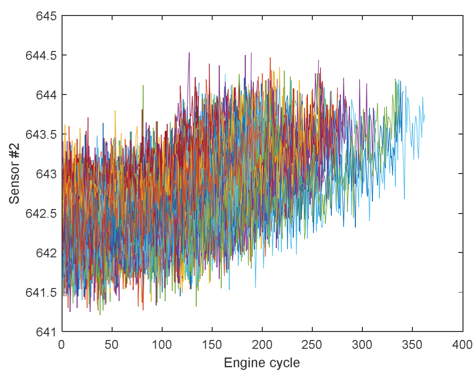


Figure 2. Degradation data for all monitoring units on sensor #2.

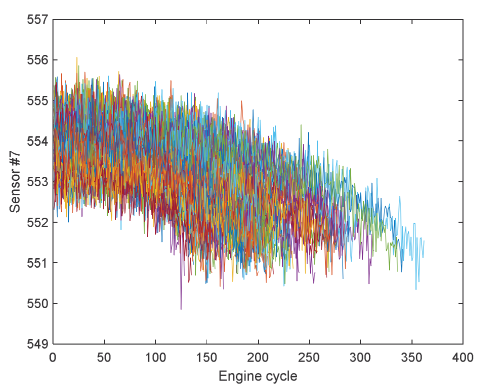


Figure 3. Degradation data for all monitoring units on sensor #7.

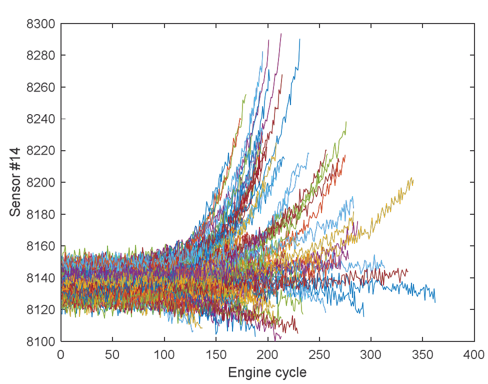


Figure 4. Degradation data for all monitoring units on sensor #14.

Step 3: Normalize the training and testing set in the raw data. The normalization is carried out by the formula $x^* = (x - x_{\min}) / (x_{\max} - x_{\min})$, where x is the raw data, $x_{\max}$ and $x_{\min}$ is the maximum and minimum value of each engine cycle for each sensor respectively.

Step 4: Training stacked denoising autoencoder. The structure of a single denoising autoencoder (DAE) is shown in Figure 5. When training a single DAE, assume that the input data is x, the autoencoder will generate $\tilde{x}$ by destroying the input data, then use the difference between the reconstructed data z generated by $\tilde{x}$ and the original input x as the reconstruction error for training.

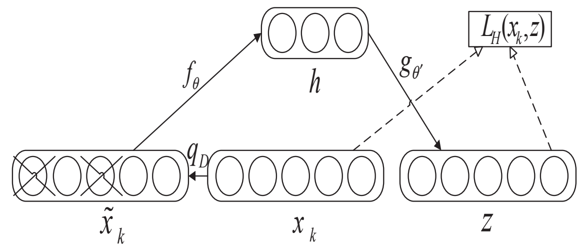


Figure 5. Structure of a single DAE.

The SDAE structure for the HI construction of the turbine engine is shown in Figure 6. A total of 4 DAEs are included, in which the first two DAEs form an encoding network, and the last two constitute a decoding network, the encoding network output is the final extracted feature. The structure adopted in this paper is 14-7-1-7-14, where 14 is the 14-dimensional sensor value of the engine data, 14-7-14 and 7-1-7 respectively constitute the two DAEs corresponding to the input layer and the output layer of the coding network in the figure. The number of features finally extracted by the coding network is 1, which is directly used as the engine health indicator value at a single point in time.

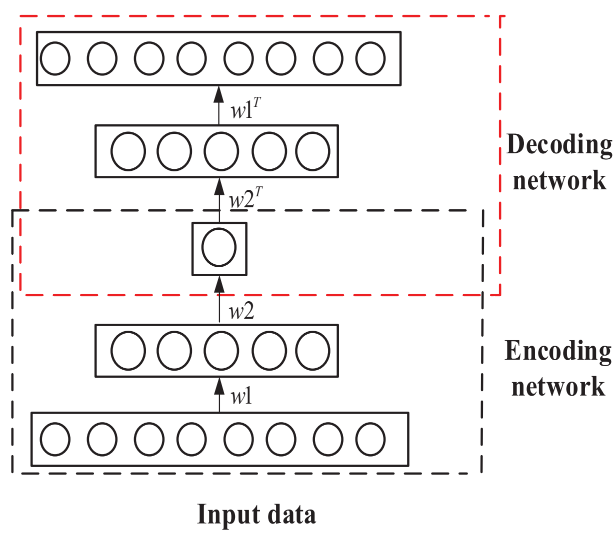


Figure 6. The structure of the SDAE in this paper.

SDAE performs unsupervised pre-training of the DAE in the encoding network on the training set one by one, and the hidden layer output is trained as the input of the next autoencoder. Then, in the decoding network, the weight of the network is directly taken as the transposition of the pre-trained weights of the relative position. Finally, the original value of the training set is used as the label, and the parameter is finetuned by the BP algorithm. The specific principles and details of SDAE can be referred to [12].

Step 5: Testing set verification. The testing data is input into the trained network for adaptive feature extraction, and the corresponding health indicator value at each engine cycle can be obtained, which forms the HI curve. All the HI curves are smoothed by a window size of 15 to reduce local noise. Finally, the HI curve construction results are evaluated.

Step 6: Algorithm evaluation. In order to quantitatively evaluate the performance of HI construction method in this paper, two commonly used evaluation indexes are selected, namely, time correlation and monotonicity [13]. The former characterizes the HI value of the turbine engine and the linear correlation of the sampling points, while the latter measures the monotonous trend of the HI curve. The definition is as shown in equations (1) and (2).

$$Corr_i = \frac{\left|\sum_{t=1}^{T_i}\left(y_{ti}-\overline{y_i}\right)\left(l_{ti}-\overline{l_i}\right)\right|}{\sqrt{\sum_{t=1}^{T_i}\left(y_{ti}-\overline{y_i}\right)^2 \sum_{t=1}^{T_i}\left(l_{ti}-\overline{l_i}\right)^2}} \tag{1}$$

where y_{ti} represents the health value of the ith curve of the i-th monitoring unit at the t-th cycle, l_{ti} represents the number of the i-th monitoring unit turbine engine cycle, T_i is the monitoring unit HI curve length, $\overline{y_i}$ is the corresponding average value of HI at each cycle of the HI curve, $\overline{l_i}$ is the average of the cycle numbers.

$$Mon_i = \left|\frac{Num\ of\ dF_i > 0}{T_i - 1} - \frac{Num\ of\ dF_i < 0}{T_i - 1}\right| \tag{2}$$

where dF_i is the differential between the sequence values in the health factor curve of the i-th monitoring unit.

Finally, the average value of time correlation and monotonicity of each HI curve is taken as the evaluation index.

The degraded state modeling method of the turbine engine proposed in this paper does not need to use complex evaluation criteria to select the sensor information, the trend of the monitoring signal can be directly observed. The whole process is carried out in an unsupervised manner without manual label design, and the adaptive feature extraction of the original multi-dimensional monitoring data is performed directly without relying on expert experience and signal processing technology, which make the proposed method have good universality and practicality.

III. Experimental Verification and Analysis

The method of modeling the degradation state of turbine engine based on SDAE is presented in Section II, and the implementation steps are introduced. In this section, the turbine engine public dataset is used for method validation, and the construction results of the HI curve will be compared with the existing methods to verify the effectiveness of the proposed method.

A. Data Introduction and Data Preprocessing

This project uses the aircraft engine simulation state public dataset provided by NASA's Prognostics Center of Excellence (PCoE) -- CMAPSS [11]. Files named "train_FD001" and "test_FD001" provided by the dataset are used as the training set and testing set for HI construction. The training set and the testing set both include 100 monitoring units, each of which has a different time series length. The training and testing set includes 20,631 and 13,096 engine cycles, respectively, and all units degenerate from varying degrees of slight loss.

According to Section II, select the sensor signal with trend in the monitoring signal and remove the sensor signal with unchanged trend.

B. Experimental Setup and Results

Firstly, the original data is normalized to the [0,1] interval. Then, the SDAE is pre-trained layer by layer, and the BP algorithm is used to fine tune the overall network parameters. After the training, the testing data is directly input to construct the HI curve on the training set and testing set.

It is known that the number of hidden layer nodes has a great influence on the feature extraction ability of the deep learning model. Usually, it is more reasonable to set the number of hidden layer nodes to 0.5 to 1.5 times of the input layer node. This fact is also applicable to the SDAE, in this paper, the network structure of the SDAE is selected as 14-7-1-7-14 by combining the specific experiment with the grid search for better parameters. The number of input layer nodes corresponds to the 14-dimensional sensor value recorded at a single sampling point, and the number of nodes in the coding network output layer corresponds to the finally extracted feature, that is, the health indicator value. The number of pre-trainings for a single DAE is 20, the noise rate is 0.05, the learning rate is 1, and the number of global network reverse tuning is 20. After the model training is completed, the normalized testing data is input into the SDAE for adaptive feature extraction, and the single feature extracted at each sampling point in the engine degradation process is taken as the HI value, thereby obtaining the final Constructed HI curve. The final HI curves of the training and testing data are shown in Figure 7 and Figure 8.

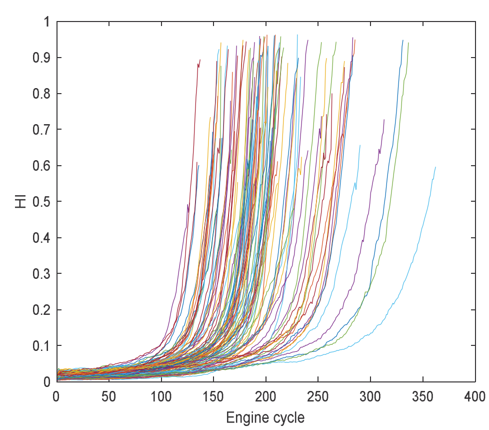


Figure 7. Turbine engine training data HI curve.

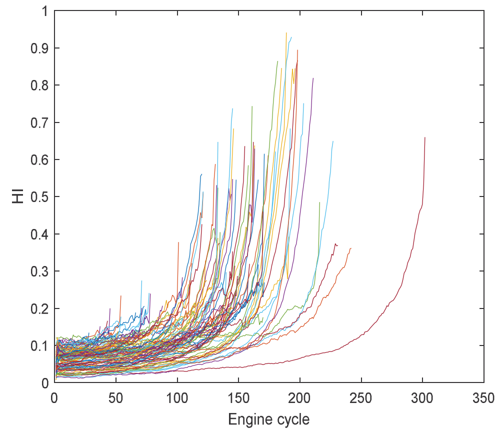
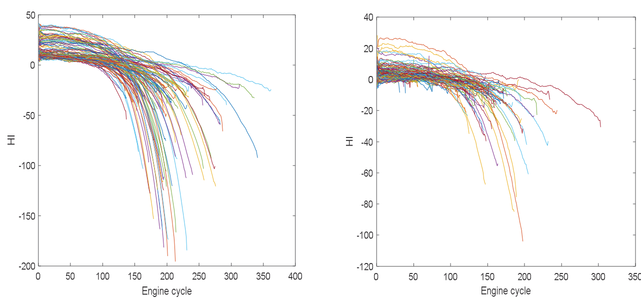


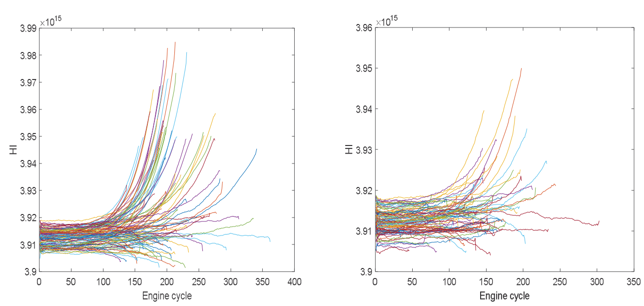
Figure 8. Turbine engine testing data HI curve.

In order to verify the advantages of this method, the HI curves are constructed using PCA and ELM_AE (extreme learning machine autoencoder, ELM_AE) methods for comparison. References for the two methods are given in [3] and [14]. PCA constructs the HI curve by extracting the maximum principal component value from the original multi-dimensional sensor information, and ELM_AE also uses the 14-7-1 network structure to extract a single node value as HI.



(a) Training set HI curve (b) Testing set HI curve

Figure 9. PCA-based turbine engine HI construction results.



(a) Training set HI curve (b) Testing set HI curve

Figure 10. ELM_AE-based turbine engine HI construction results.

Figure 9 and Figure 10 show the HI curves constructed by the two methods of PCA and ELM_AE. It can be seen from the figure that the PCA-based HI construction results show a monotonous downward trend, but the noise is obvious, and the HI curves of different monitoring units are quite different. While the HI construction results based on ELM_AE have inconsistent monotonicity of the curve, large noise and some curves cannot reflect the degradation process. Compared with the HI curves constructed by these two methods, the HI curve in this paper is smoother, more monotonous, and less noisy.

TABLE II. TURBINE ENGINE HI CURVE EVALUATION INDEX RESULTS

Turbine engine data	PCA		ELM_AE		Proposed method	
	Corr	Mon	Corr	Mon	Corr	Mon
Training set	0.844	0.060	0.696	0.058	**0.892**	**0.637**
Testing set	0.516	0.054	0.426	0.049	**0.825**	**0.428**

In order to further evaluate the HI curve results constructed in this paper, Table II gives the evaluation index values of the HI curves constructed by the three methods. The quantified index values of the training set and the testing set in the table are the average results of 100 HI curves. It can be seen that the results of the quantitative indicators of the turbine engine HI curves based on SDAE on the training set and the testing set are significantly better than the other two methods. To sum up, the multi-dimensional turbine engine data degradation state modeling method based on SDAE in this paper achieves a better HI curve construction result, which can better reflect the degradation process of engine health status compared with the traditional signal feature extraction method.

IV. CONCLUSION

In this paper, a new unsupervised HI construction method of turbine engine based on SDAE is proposed. The construction process of HI curve is illustrated in detail by example, and the experimental results are compared with that using PCA and ELM_AE, which are typical multi-sensor degradation state modeling methods. The experimental results on the CMAPSS turbine engine dataset show that the proposed SDAE-based degradation state modeling method has better time correlation and monotonicity, the curve is smoother and the noise is smaller, which can better reflect the engine degradation process of engine health status. In addition, the proposed method does not rely on excessive expert experience and complex signal processing techniques, and its unsupervised learning manner makes it more versatile.

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