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An aero-engine remaining useful life prediction model based on feature selection and the improved TCN[☆]

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ABSTRACT

Inferring the remaining useful life (RUL) of an aero-engine based on complex data from aircraft sensors is one of the important issues to ensure flight safety. To this end, this paper is intended to propose a RUL prediction model based on the feature extraction method and the improved temporal convolution network (TCN). First, the XGBoost (eXtreme Gradient Boosting) model is used to assess the importance of the data and filter the features base on the resulting correlation. Then, the RUL prediction model is constructed by paralleling TCN networks with different expansion rates, which expands the receptive field and further improves the information obtained by the network from the data. Moreover, the network is further optimized with dynamic hyperparameter search methods. Finally, through comparative experiments, the proposed prediction model is evaluated based on the turbofan aero-engine operation failure prediction benchmark dataset (CMAPSS). The experimental results show that by deleting some data with low correlation, the proposed model can achieve better prediction accuracy, which is superior to other mainstream models in the references.

1. Introduction

RUL is a period of time that the aero-engine can be in a healthy state and can operate safely and stably. Accurately estimating the RUL of the aero-engine is key to ensuring the safe operation of the aircraft[1]. Through different sensors, various parameters during aero-engine operation can be obtained, which provides the basis for predicting the RUL of the aero-engine. However, the relationship between these data and the operating state of the aero-engine is high dimensional and complex, and therefore it is difficult to establish an accurate model to obtain the RUL [2].

At present, the problem of the RUL prediction has been solved mainly based on the physical modeling and data-driven methods. Among them, the physical modeling method builds models by acquiring features in the time or frequency domain to obtain the health status of the mechanical system, thereby achieving the RUL of the system in the current state [3–5]. The work [4] processed the vibration data of 11 gearbox operating to fault, calculated the fault growth parameter (FGP) from the residual signal, and constructed a degradation model to obtain the RUL of the gearbox. The RUL of the slurry pump impeller was estimated by extrapolating the established state space model based on the moving-average wear degradation index to a specified alert threshold in [5]. The physical modeling method has strong explanatory nature, but many parameters need to be considered, which brings difficulties to modeling.

The data-driven approach mainly analyzes the past data of the mechanical system to obtain the current operating status and predict the RUL, which can get high-precision results by mining massive data [6–10]. The paper [6] has proposed a degradation model with flexible random-effects used in the field of degradation modeling and RUL estimation. The relevance vector machine (RVM) is employed to predict survival probability of individual unit of machine component in [7]. The work [8] has adopted a probabilistic method called particle filter to predict the RUL of gas turbines. In [9], by utilizing system-level observation history, a dynamic reliability assessment method for multi-state system is put forth to predict the RUL based on the recursive Bayesian formula. The work [10] has presented a data-driven algorithm based on an ensemble of Auto-Regressive (AR) models and classifiers to predict the system's state evolution, while the work [11] has proposed a similarity-based Particle Filter (PF) method for the RUL prediction with improved performance. Nevertheless, the traditional data-driven approach cannot import more data for analysis because of the simple model.

In recent years, with the rise of artificial intelligence, more and more scholars have devoted themselves to studying the use of deep

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learning algorithm for RUL prediction of aero-engine, and have made some progress. Due to the obvious characteristics of long-time series, several achievements have been made by using RNN and other deep learning models to process time series data [12,13]. The CNN-RNN model used in [14] to solve the problem of information loss in RNN in the long-term sequence model and the accuracy of RUL prediction has been improved. Later, in order to solve the problem of gradient vanishing during the training of RNN, more complex models based on LSTM and GRU have been introduced to solve RUL prediction problems [15, 16]. Then BiLSTM network has been proposed for RUL estimation, which can make full use of the sensor date sequence in bidirection [17, 18]. The paper [19] has proposed a new data-driven approach for prognostics using deep convolution neural networks (DCNN), and high prediction accuracy on the RUL estimation has been achieved. In [20], the attention mechanism has been applied to predict the RUL, which is able to capture more information in long sequences and achieve better prediction accuracy. Furthermore, the work [21] has proposed a new attention-based deep convolutional neural network architecture to predict the RUL of turbofan aero-engines, which can better extract features from multivariate time series.

In the abovementioned results, all the features obtained by the sensor are taken as the input of the neural network. Different features have different effects on the RUL of the aero-engine, and the RUL prediction based on features with low correlation may be counterproductive. Moreover, too many input features will slow down the training speed of the model. Therefore, it is very important to select the features with high correlation with the RUL of the machine as the model input for the prediction. Various feature selection methods have been widely used in different fields to improve the accuracy of corresponding work [22–26]. PCA is a commonly used data dimensionality reduction algorithm. The work [22] has analyzed the basic principles of PCA and used it to verify its feasibility in datasets containing biological, safety, and chemical fields. For the RUL prediction problem, the work [23] has screened the features through PCA and trained them with the random forest (RF) algorithm, which has achieved good prediction results. Maximal-information-coefficient (MIC) is used to screen and weight p-value to reduce dimension in high-dimensional situations [24]. In the sediment lead (Pb) prediction problem, the data are filtered by XGBoost, and the information lost in the model training stage is reduced, resulting in better prediction effect [25]. In terms of predicting the RUL, a linear reliability indicator approach has been put forward in [26], where multiple deep auto-encoder models are established to extract deep features, and a clustering method is employed to select the original feature set. In addition, the work [27] has proposed an intelligent RUL prediction approach for aero-engine by integrating multimodal data fusion methodology and ensemble transfer learning technology. This method has performed a robust RUL prediction under cross-working conditions by dynamically selecting sensing data.

As everyone knows, the structure of TCN makes it able to obtain more information on historical data of different lengths. Consider that the RUL prediction studied in this paper is a multi-time series prediction problem, and excessive data may contain a large amount of noise, which will affect the training effect of the model. Therefore, in order to obtain better prediction effect, this paper proposes an aero-engine RUL prediction model based on the feature selection and the improved TCN. The main contributions are as follows:

i. Since the already operating cycle of aero-engine is closely related to the state of the aero-engine, it is used as an extra input feature to train the RUL prediction model.
ii. The input features of the model are screened out through the importance evaluation results given by the XGBoost algorithm, which can reduce the noise and improve the prediction accuracy.
iii. The improved network based on TCN is proposed by superimposing the outputs of multiple networks to obtain information from different sensory domains.

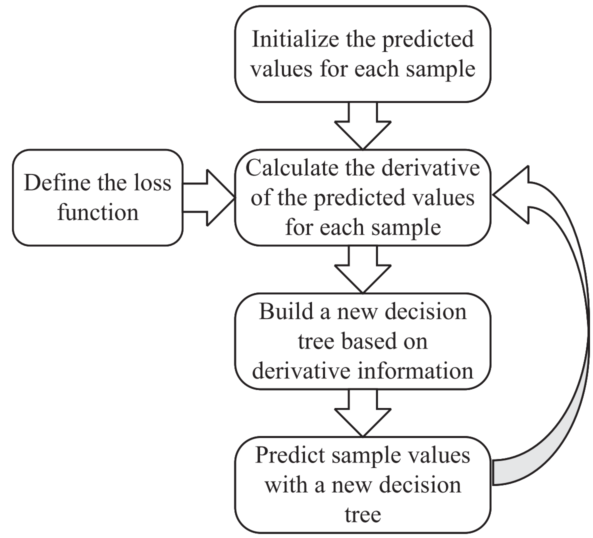


Fig. 1. The flowchart of the XGBoost algorithm.

2. Related theories and its applicability analysis

This section mainly focuses on the theoretical part related to the proposed aero-engine RUL prediction model.

2.1. XGBoost

XGBoost is an algorithm or engineering implementation based on Gradient Boosting Decision Tree (GBDT). The basic idea is the same as that of GBDT, but some optimizations have been made. For example, the second derivative is added to make the loss function more accurate, the regular terms are adopted to avoid tree overfitting, and the block storage can be computed in parallel, etc. Therefore, the XGBoost algorithm is efficient, flexible and lightweight, which is widely used in data mining, recommendation systems and other fields.

In this paper, the XGBoost algorithm is used to get the importance of each sensor data and to filter the features based on the resulting importance. The overall flowchart of the XGBoost algorithm is shown in Fig. 1. First, initialize the true value of each sample. According to the determined loss function, the first and second derivatives corresponding to the predicted value of each sample can be calculated. Then, the new decision tree will be built based on the derivative information. Finally, by repeating the above process, a decision tree with the predicted value meeting the requirements can be obtained.

In the problem of the aero-engine RUL prediction, the number of features acquired by sensors is very large. Thus, by using the XGBoost algorithm to get the importance of each feature, the ones with high correlation can be selected, which can further improve the prediction accuracy.

2.2. The improved TCN

TCN was proposed in 2018 and has been widely used in various fields. Fig. 2 shows the main structure of TCN, which consists of the causal convolution and the residual block. Unlike the cyclic architecture, TCN has a backpropagation path that is different from the sequence time direction, thus avoiding the problem of gradient explosion or disappearance in RNN [28]. As shown in the figure, the output at time t depends on the data at time t and before it, which allows TCN to obtain relevant information from the data from the historical data. At the same time, the residual block makes the network structure deeper to avoid the problems of gradient explosion and gradient disappearance. Compared with the traditional residual structure, a 1*1 convolutional

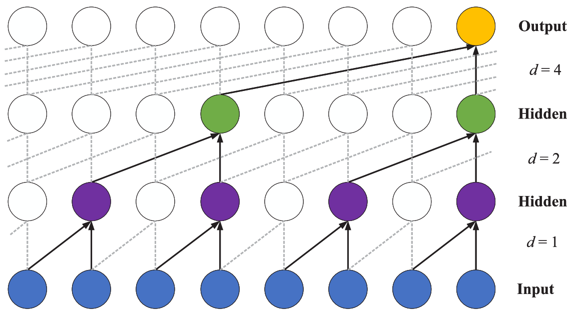


Fig. 2. The structure diagram of TCN.

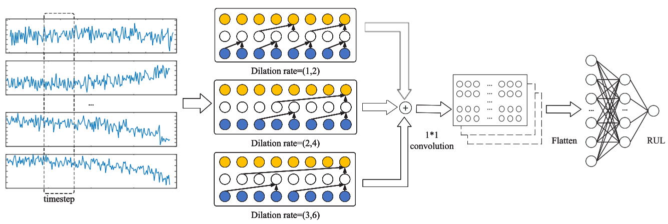


Fig. 3. The structure diagram of the RUL prediction model based on the improved TCN.

layer is added to TCN to solve the problem of different input and output widths, so that the network obtains tensors of the same shape. Thus, the subtle structure of TCN enables it to obtain sufficient historical information and improve the efficiency of operation.

The problem studied in this paper is to predict the RUL of the engine according to the values of different sensors. However, the decline in engine life is not sudden, the responses to different sensor values are different, and will not occur at the same time. Using a single TCN network cannot learn the information transmitted by different sensor data changes at the same time. So, we have strengthened the model's recognition of different data changes by paralleling three TCNs with gradually increasing dilation rates (1,2), (2,4), and (3,6) to obtain information under different receptive fields. For example, the dilation rate (1,2) means that the dilation rate of the first layer of the TCN is 1, and the second layer is 2. Thus, this proposed model can learn different sensor changes and engine degradation status, and achieve higher accuracy. To further enhance the network's ability to extract information from data, the improved TCN structure is proposed in this paper. As shown in Fig. 3, the overall structure consists of the TCNs with different expansion rates, a convolutional layer with 1*1 convolution kernel and a fully connected layer. First, the input passes through the TCNs with different expansion rates, and more useful information in the time series can be obtained. Then, the corresponding outputs of multiple TCNs are superimposed, and the dimension is reduced by the 1*1 convolutional layer. Finally, the predicted RUL can be achieved through the fully connected layer. The improved TCN can obtain different field information through different expansion rates, which is significant for the RUL prediction of the aero-engine.

3. The proposed RUL prediction model

Based on the feature selection algorithm and the improved TCN structure, this section will give the detailed process of building the RUL prediction model.

3.1. Modeling process

To improve the accuracy of the RUL prediction, the XGBoost algorithm is utilized to select features according to the obtained importance.

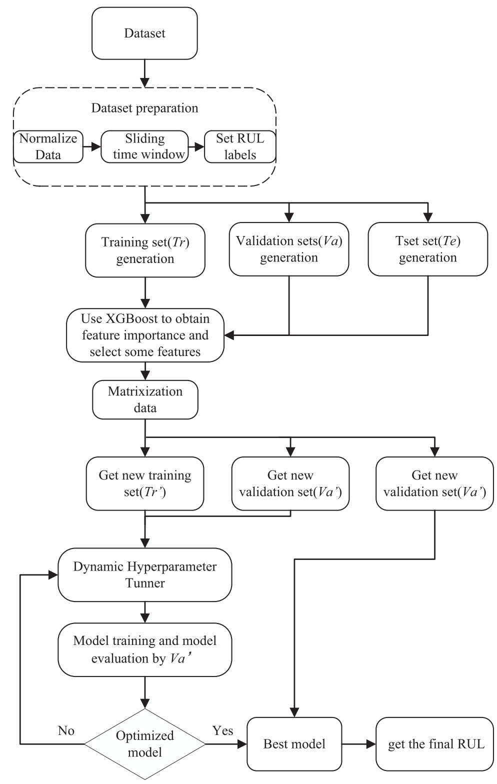


Fig. 4. Model flowchart.

Moreover, the improved TCN model with different expansion ratios is built to better mine the laws in long-term historical data. The detailed process of the proposed RUL prediction model is shown in Fig. 4.

Step 1: In order to avoid the problem caused by different data profiles of different sensors, it is necessary to normalize the data first. In this paper, the Max–min normalization method is chosen, which also accelerates the optimal solution in gradient descent optimization. The expression is shown as follows:

$$x^* = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where x_{max}, x_{min} are the maximum and minimum values in each column of data, respectively, x is the original data value before normalization.

The preprocessed data are sorted into ($timestep$, q), where $timestep$ is the length of time window, and q represents the feature dimension included in the sample at each time point. All the samples are divided into the training set (Tr), validation set (Va), and test set (Te) according to a certain proportion.

Step 2: Put the training set Tr into XGBoost to get the importance of each feature, and the top n features with higher importance are selected as the input of the constructed network. According to the input format requirements of the TCN network, it is necessary to use the sliding time window method to reconstruct the original dataset containing multidimensional features into a multi-dimensional and multi-step time series suitable for training the TCN network, which is converted into a three-dimensional matrix format (m, $timestep$, n), where m is the batch number and n is the number of features selected, the new training set Tr', validation set Va', test set Te' can be obtained.

Step 3: The training set Tr' is fed into the improved TCN model. Several strategies such as the dropout, dynamic attenuation of learning rate, early stop and dynamic hyperparameter optimization are adopted in the training process. Based on the validation set Va', the optimal prediction model for the aero-engine can be achieved.

- Dropout: During the training process, by randomly discarding some neural units, the impact of model overfitting can be reduced.
- Dynamic attenuation of learning rate: The model is trained with a large initial learning rate. As the performance on the validation set deteriorates, the learning rate automatically decreases gradually to enhance the learning ability of the model.
- Early stop: When the validation effect continues to deteriorate for several periods and the learning rate decay strategy can no longer help, it indicates that the model learning ability has reached saturation. At this time, stopping early can greatly improve the training efficiency of deep learning.
- Dynamic hyperparameter optimization: Select and determine the value ranges of hyperparameters, including the $timestep$ and k, where k represents the number of last prediction moments. In order to save resources and time, the coordinate descent algorithm is selected. First, adjust the hyperparameters that have the greatest impact on the model until optimization; Then adjust to the next parameter that has the most impact, and so on, until all parameters are adjusted.

Step 4: The RUL of each engine is defined as the corresponding RUL prediction value at the last cycle. Based on the optimal prediction model obtained through training and validation, the RUL of the engine can be obtained by using the sensor data at the current and historical times. In CMAPSS dataset, the RUL of each engine in the test set is defined as the corresponding RUL prediction value at the last cycle. If only the feature data of the last time step length are used to predict the RUL, it will increase the prediction error. Actually, based on the proposed model, we can obtain the remaining lifespan of the engine at any cycle and convert it into an equivalent RUL by subtracting the number of cycles required to reach the last one. In this manuscript, the RUL prediction results of the engine at the last k cycles have been calculated respectively. By subtracting the number of cycles required to reach the last one, the equivalent RUL prediction results can be achieved.

3.2. Performance evaluation metric

In this paper, two commonly used indicators, the scoring metric and RMSE, are chosen to evaluate the prediction accuracy of the proposed model. The detailed expressions [29] are defined as follows:

$$RMSE = \sqrt{\frac{1}{h} \sum_{h}^{i=1} e_i^2} \tag{2}$$

$$Score = \begin{cases} \sum_{i=1}^{h} (e^{\frac{-e_i}{13}} - 1), e_i < 0 \\ \sum_{i=1}^{h} (e^{\frac{e_i}{10}} - 1), e_i > 0 \end{cases} \tag{3}$$

$$e_i = y_{i\_predicted} - y_{i\_true} \tag{4}$$

where y_{i_true} and $y_{i\_predicted}$ are the actual and predicted RUL in the ith engine, respectively, h is Number of engines. In either case of formula (3), the $y_{i\_predicted}$ that diverges from the y_{i_true} is penalized exponentially, which makes the score increases exponentially with the prediction error. Moreover, the late predictions (e_i> 0) are penalized more severely than early predictions (e_i< 0), because late predictions maybe result in catastrophic failures in critical situations, and early predictions give more time for aero-engine overhaul and maintenance operations. Therefore, the smaller score means the more accurate the prediction effect and the better the model performance.

4. Experiment

In order to verify the effectiveness and advancement of the proposed RUL prediction model for aero-engine, this section conducts the experiments based on the subdatasets FD001 and FD003 of the NASA's CMAPSS dataset. In this work, the models are developed using Keras API with Tensorflow backend. The experimental environment is an AMD Ryzen 7 5800H CPU, and one Nvidia RTX 3070 laptop graphical processing units with 8-GB memory.

Table 1
The description of the subdatasets FD001 and FD003.

Name	FD001	FD003
Number of training engines	100	100
Training sample	20 630	24 720
Number of test engines	100	100
Test sample	16 596	13 095
Operating conditions	1	6
Failure type	1	1
Number of sensors	21	21

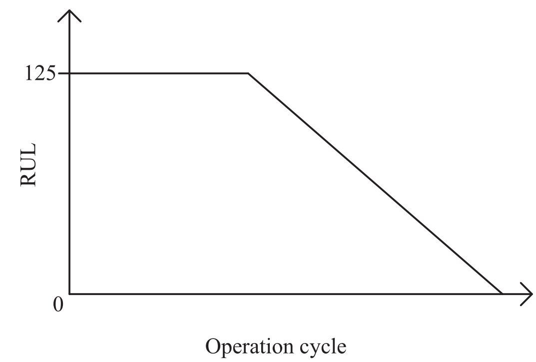


Fig. 5. RUL function.

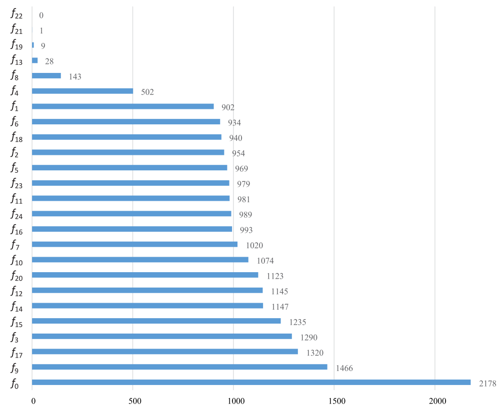
4.1. Dataset description

The CMAPSS dataset is an open dataset that contains 21 sensors and 3 operating status data for several aero-engines in each operating cycle. The sensors record data such as the rotation speed and temperature of the rotating blades and other parts of the aero-engine. Both the subdatasets FD001 and FD003 contain data from 100 aero-engines in a variable operating state and a fault condition. Each of the two subsets contains a training set and a test set. The detailed information is shown in Table 1. As the operating time of the aero-engine increases, the probability of failure will also increase, resulting in the decrease of RUL. The cycle that the aero-engine has been running may be important to the RUL prediction and therefore it is selected as an additional input feature to train the RUL prediction model.

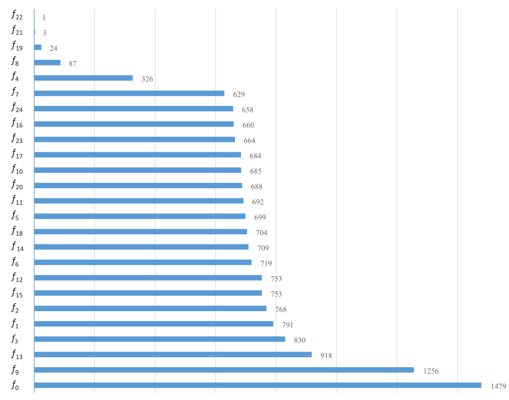
The task of estimating RUL involves determining the remaining operating cycle before the aero-engine fails. In the early operation period, the aero-engine is in good condition with little degradation, and the RUL can be regarded as a fixed value. In the later stage of the aero-engine operation, the failure rate increases and the aero-engine degrades significantly. Therefore, 125 is selected as the threshold value, and the defined RUL function for the aero-engine is shown in Fig. 5. It means that when the remaining operating cycle of the aero-engine is greater than 125, the RUL is regarded as 125 unchanged, otherwise, the RUL will decrease with the operating cycle.

4.2. Evaluating feature importance

According to the proposed aero-engine RUL prediction model in Section 3, the importance of all the features including 21 sensor data, 3 operating status data and the cycle already running need to be assessed before training the model. First, the original dataset is normalized by using the Max–min normalization and reshaped into the form ($timestep$, q), where the value range of $timestep$ is set to be [25, 40], q is represents the feature dimension included in the sample at each time point. Then, the Based on the training set, the XGBoost algorithm is adopted to evaluate the importance of all the features and the results for these two datasets are shown in Figs. 6a and 6b respectively. Moreover the parameter settings of XGBoost are shown in Table 2.



(a) FD001



(b) FD003

Fig. 6. The evaluated importance for all the features.

Table 2
The parameters of XGBoost.

Parameters	Value
Booster	gbtree
Objective	reg:gamma
Gamma	0.1
max_depth	5
Lambda	3
Subsample	0.7
min_child_weight	3
eta	0.1

In the figure, the ordinate represents the feature sequence number, where f_0 is the cycle that the aero-engine has run, f_1-f_3 are the operating condition of the aero-engine, and f_4-f_{24} are the features obtained by 21 sensors of the aero-engine. The abscissa is the evaluated importance for all the features. It can be seen from both Figures 6a and 6b that the importance of f_0 far exceeds other features, which means the cycle of aero-engine operation is the most critical factor affecting the RUL. With respect to the subdataset FD001, the importance values of f_{22}, f_{21}, f_{19}, f_{13}, f_8, f_4 are very low, while the rest are all above 900. Similarly, for the subdataset FD003, except for the relatively low importance values of the five features, all other importance values are above 600. Thus, it is difficult to determine the specific threshold. In order to achieve better prediction effect, this paper selects the number of features q as a hyperparameter when training the model, and the setting range is [10,20]. The most suitable number of features will be obtained based on the final training result.

Table 3
The parameters of the model.

Parameters	Value
Number of epochs	100
Learning rate	0.001
Optimizers	Adam
Loss function	MSE
Early stopping/patience	True/100
TCN dilation rate	(1, 2), (2, 4), (3, 6)
number of filter	10, 10, 10
CNN convolutional kernel number	(1, 1)*1
Dense neuron nodes	32, 1

Table 4
The optimal hyperparameters and the evaluation indicator under different number of input features.

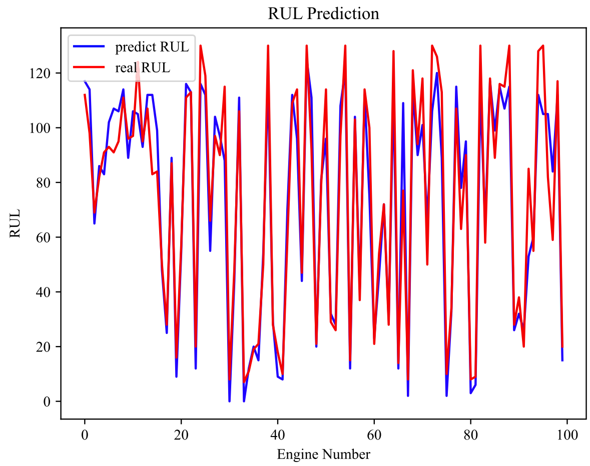
Number of features	FD001			FD003		
	Timestep	*k*	Score	*Timestep*	*k*	Score
20	28	10	214.36	40	3	201.25
19	34	11	197.26	40	6	210.61
18	29	3	199.44	37	3	193.02
17	37	14	203.05	38	8	189.26
16	26	6	231.60	40	4	211.97
15	37	12	234.54	40	3	194.02
14	39	4	213.10	39	6	224.52
13	34	1	198.53	39	3	209.42
12	39	10	194.04	40	7	202.87
11	40	6	194.87	40	3	210.27
10	28	11	215.39	39	5	204.21

4.3. Model training and results

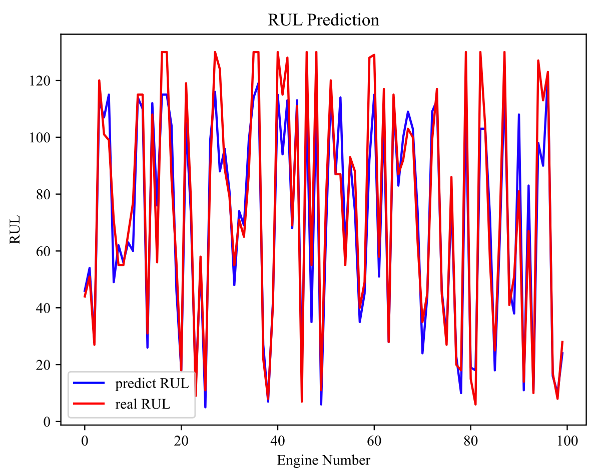
The parameter settings of the proposed model are shown in Table 3. According to the selected hyperparameter n, the dataset is reconstructed and the new training and test set are obtained. Extract 20% of the training set data to get the validation set. Based on the training and validation sets, the proposed prediction model is trained with the dropout, dynamic attenuation of learning rate and early stop. At the same time, with $k \in [1, 15]$ and $timestep \in [25, 40]$, the dynamic hyperparameter optimization can be achieved through the grid search method. In the experiment, 200 rounds of hyperparameter optimization have been conducted. Among them, each round of model training includes 100 epochs, which takes about ten minutes.

Therefore, with respect to different numbers of input features, the optimal hyperparameters k and $timestep$ can be obtained according to the $Score$ calculated based on the prediction results of the validation set. Based on the corresponding optimal prediction model, the RUL of all engines in the test set can be calculated and the indicator 'Score' are shown in Table 4. From the evaluation results, one can conclude that for the subdataset FD001, the test set has the best prediction performance when selecting the features with the top 12 importance rankings as the input of the model, where the $timestep$ is 39 and k is 10. In the same way, with n=17, $timestep$=38 and k =8, the score of the test set of the subdataset FD003 can reach the minimum value of 189.26.

Fig. 7a and b show the RUL of 100 engines in the test set of these two subdatasets. Among them, the horizontal axis represents the aero-engine number, and the vertical one is the RUL value. In these two figures, most of the red and blue lines coincide, indicating that the predictions of RUL for most aero-engines are accurate. In order to more intuitively display the RUL prediction results of a certain machine throughout the entire operation process, two certain engines form the test sets of these two subdatasets respectively are selected and the RUL prediction curves are shown in Fig. 8. The red line and the blue line represent the real RUL and the predicted one of the engine in each cycle, respectively. The figures show that the predicted RUL curve is basically consistent with the real one in the overall trend. However,

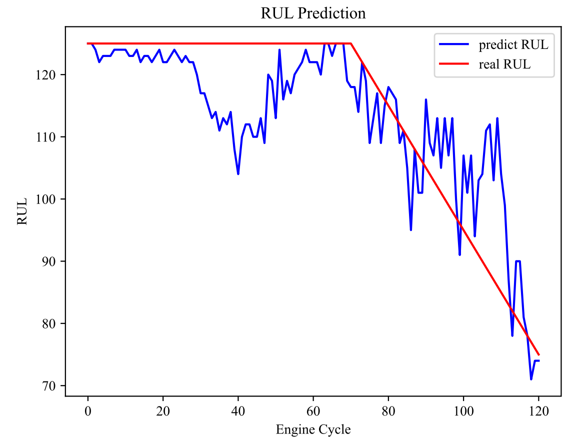


(a) machine of FD001

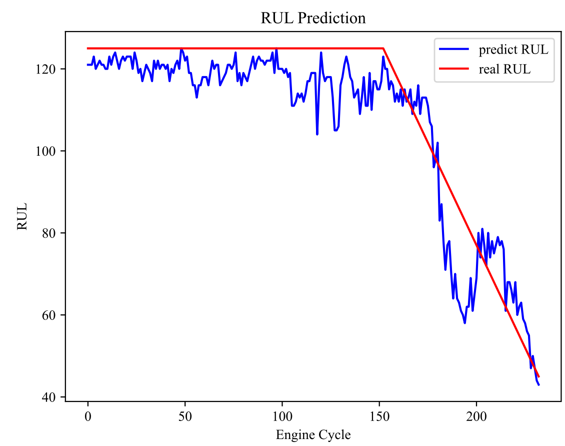


(b) machine of FD003

Fig. 7. The RUL prediction results for all the engines in the test set. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)



(a) FD001



(b) FD003

Fig. 8. The RUL prediction curves for certain engines in the test set.

there is a significant deviation in the RUL prediction for the engine in the subdataset FD001 under healthy operation state, while there exist some errors in the prediction results of the engine in the subdataset FD003 in a degraded state. This is due to the existence of noise in the data, and the model may be difficult to judge the operating state of the aero-engine.

Furthermore, the prediction effect is compared with other mainstream deep learning models to verify the superiority of the proposed model. Specifically, in DCNN [19], four stacked convolution layers with dropout layers were used to reduce overfitting. BiLSTM [17,18] has the capacity to exploit long-range information in both input directions. Double Attention [30] was used to focus attention on these features at critical time steps. RBPF [11] is employed to update the degradation states based on the initialization. KGHM [31] represents the sensor relationships as flow charts to be transformed as embedding vectors for clustering.

The comparison results of the evaluation indicators are shown in the Table 5. With respect to the subdataset FD001, the RMSE and score of the proposed improved TCN model on the test set are 11.74 and 194.04, respectively, which are lower than the existing results. And in the test set of FD0003, the RMSE and score are 12.19 and 189.26. It means that the proposed model is superior to other ones in terms of score and RMSE, and has better prediction accuracy.

Table 5
Comparison results of the evaluation indicators for different prediction models.

Model	FD001		FD003	
	RMSE	Score	RMSE	Score
DCNN [19]	12.61	273.70	13.61	284.10
BiLSTM [17]	13.65	295	13.74	317
BiLSTM+ED [18]	14.47	273	12.10	574
RBPF [11]	15.94	383.39	16.17	375.29
KGHM [31]	13.18	250.99	13.25	333.44
Double Attention [30]	12.25	272.17	13.39	290
TCN	14.27	254.80	14.99	330.54
The improved TCN	11.74	194.04	12.19	189.26

5. Conclusion

In this paper, the RUL prediction problem for the aero-engine has been solve by adopting the methodology of feature selection and the deep neural network. On one hand, the XGBoost algorithm is used to assess the importance of each feature, which can better show the correlation with the RUL. On the other hand, an improved deep learning model based on TCN is introduced to obtain more information on a long time series by paralleling TCN networks with different strides. The model is evaluated on the CMPASS dataset, and both RMSE and score indicators have achieved better results compared with the recently existing models.

However, certain limitations still exist. It cannot be denied that there is still room for further improvement in the prediction method proposed in this work. For example, this paper only filters the sensor data, and does not deal with the possible noise in the data. At the same time, the number of layers and expansion rate of TCN may not be deep enough. In our future work, we will focus on addressing these issues to enhance the prediction accuracy.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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