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An Automatic Data Augment Method for Remaining Useful Life Prediction of Aeroengines

Zequan Wang*, Hanqing Zhou, Jianfeng Yang, Xing Ding

China Aero-Polytechnology Establishment, Beijing 010020, China

*Corresponding to; Zequan Wang

Abstract. The prediction of remaining service life in complex aviation engine systems is of great significance for airlines to develop maintenance plans for engines and reduce maintenance cost. However, the complex operating conditions of the engine and insufficient fault mode data limit the prediction accuracy. One direction to solve such problems is data augmentation, which aims to generate synthetic data from real datasets to expand training samples and improve the model's generalization ability. Admittedly, there are already many mature data augmentation methods, but the optimal data augmentation strategy for RUL prediction tasks varies in different situations. Confirming which data augmentation strategy is most suitable for the current remaining useful life prediction problem requires human experience or extensive parameter experiments. This work proposes an automatic data augmentation method(AdaRUL),Build an automatic search space and use reinforcement learning algorithms to search for the optimal strategy in the automatic search space to expand the sample dataset. The experiments conducted on the C-MAPSS public dataset provided by NASA demonstrate that AdaRUL has successfully generated high fidelity multivariate monitoring data. In addition, these generated data effectively support RUL prediction tasks and significantly improve the predictive ability of underlying deep learning models.

Keywords: Remaining Useful Life Prediction; Data Augment; Reinforcement Learning; Deep Learning

1 INTRODUCTION

Aircraft engines are one of the most important and complex parts of an aircraft, and their failure can pose a serious threat to flight safety. Therefore, it is of great significance to estimate the useful life of aircraft engines - that is, to accurately predict the time when failure happened. In recent years, methods of estimating the remaining useful life(RUL) of aero engines have gradually shifted from physics-based methods to data-driven deep learning methods[1-2]. A number of studies have shown that the problem of remaining useful life prediction in complex industrial system environment can be effectively solved by training machine learning prediction models using the data of working conditions obtained from sensor measurements as datasets [3,4,5]. Multiple models such as LSTM[6], RNN[7], Transformer[8] perform well in scenarios dealing with evolving spatial degradation patterns. For example, Muner[9] proposed an attention based deep convolutional neural network (DCNN) architecture to predict RUL for turbofans. Predictability measures are used for feature ranking and selection, while time window methods are used for sample preparation to take advantage of multiple temporal information for better feature extraction via an attention based DCNN model, solving the problem of loss of accuracy in traditional models in long time series prediction problems. Zhizhen Zhang[10] proposed the dual aspect self attachment framework based on transformer, which effectively solved the problem of variable interactions under complex operating conditions, and in long-term series data, the model was able to focus more on more major input dimensions.

Although a large number of studies have explored the application of deep learning techniques to the problem of remaining service life prediction, few have worked to solve the problem of data shortages faced in the development of data-driven models. It is well known that the accuracy and effectiveness of deep learning models depend heavily on the availability of mission data sets[11]. However, aero engine failure monitoring is difficult and data acquisition is difficult, so it is still difficult to obtain a complete set of long-period engine failure data[12].The most typical is a data generation strategy based on the Generation Countermeasures Network (GAN) proposed by Goodfellow [13]. GAN uses game theory to generate virtual datasets that are highly similar to the experimental datasets, with good results on multiple datasets. In RUL prediction studies, GAN can be used to generate data.

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Huaqing Wang et al. [14] et al. proposed using the GAN model to extend the signature signature computed in time domain from the original vibration in the bearing remaining service life prediction data set, and the generated data better represent the bearing degradation state. Ji Shang[15] designed a dense convolutional regression network (DCRN), improving the mode collapse problem.

Overall, good progress has been made in the data augment framework for remaining service life prediction, but these data augment methods tend to perform well only in the RUL mission of the current artifact or category. In other words, designing a data augment strategy capable of the vast majority of RUL prediction tasks is extremely challenging. A major reason for this problem is that in complex industrial manufacturing scenarios, the operating conditions are complex, and the types of sensor data vary widely when fault data is acquired for different industrial products[16]. This results in still relying on personal experience to artificially select data augment models for RUL predictions.

In recent years, Automatic Data Augmentation (AutoDA) [17-19] has been used in the field of image data augment and has achieved prospective results. Automatic search strategy is a data augment strategy search algorithm based on reinforcement learning method. It uses a pair of reinforcement learning algorithms to find the optimal data augment algorithm in the search space by constructing the search space, thus solving the problem that there is always a need for human to select the data augment strategy in RUL prediction to some extent. While it is true that AutoDA has good research value because of its superior performance in automatically selecting augment strategies, the computational cost of the model is too large due to the large search space that the model needs to construct during the training process. In addition, the problem of selecting the AutoDA strategy for time series data augment remains to be studied.

In the above discussion, a light automatic data augment method for aero engine remaining service life prediction is proposed, which can construct a search space for RUL time series data augment strategy and design a controller model to constantly search for the optimal search strategy in the search space. As the controller converges, the controller outputs an optimal search strategy that is used for the current RUL mission for data enhancements.

Specifically, the contributions of this article are as follows:

The paper proposed a strategy capable of automatically searching for optimal data augment algorithm for aeroengine RUL prediction tasks under different operating conditions and failure modes(Automatic Augmentation Data Augmentation Method for RUL, AdaRUL). It is also used to predict the remaining service life of aero engines. A new perspective is introduced to solve the problem of aero engine failure prediction with less data.

Considering the problem of excessive search space of automatic search strategy in image defect monitoring, this paper constructs a lightweight time series data augment algorithm search space for aero engine prediction problem, which greatly reduces computational cost. In this search space, each strategy consists of two sub strategies. At the same time, a complete data set is divided into multiple sub data sets, each of which randomly selects a sub strategy for data enhancement. Each sub strategy consists of three parts: the data augment algorithm, the probability of applying the algorithm, and the function parameters. Search algorithms find the optimal search strategy in this lightweight search space, allowing the model to achieve the highest data accuracy on the validation set.

Experimental validation of the opensource dataset—C-MAPSS: AdaRUL is able to generate high-quality simulation data and can improve the accuracy of the model's prediction of the remaining service life of the aero engine.

2 PROBLEM FORMULATION

For a set of engines with the same operating conditions and the same failure mode E={n1,n2,...,nN}, The set of failure degradation data obtained by sensor measurements is defined as

$$\mathrm{X} = \{\mathrm{X}^{n_i} \mid i = 1,2,\dots,N\} \tag{1}$$

Where the failure i (1⩽i⩽N) monitoring data set for the ith aero engine is shown by formula (2):

$$\mathrm{X}^{n_i} = \{x_1^{(n_i)}, x_2^{(n_i)}, \dots, x_t^{(n_i)}, \dots, x_{Tn_i}^{(n_i)}\} \tag{2}$$

$x_t^{(n_i)} = \{x_{t,j}^{(n_i)} \mid j = 1,2,\dots,n_v\}$ represents monitoring data nv measured by sensors with an engine run period of t. And T_{n_i} represents the time step experienced by the ith engine from the start of the measurement to the failure. A set of remaining service life measurements for ith engine is expressed as $Y^{(n_i)} = \{y_1^{(n_i)}, y_2^{(n_i)}, \dots y_t^{(n_i)}, \dots y_{Tn_i}^{(n_i)}\}$, $y_t^{(n_i)}$ expressed as the time interval between the current moment t and the engine failure, as shown in equation (3):

$$y_t^{(n_i)} = T_{n_i} - t \tag{3}$$

Due to the magnitude differences between groups of time series data measured by the sensor, a maximum minimum normalization of the data is required to improve the model training rate, with the normalization process shown in (4):

$$\bar{x}_{t,j}^{n_i} = \frac{x_{t,j}^{n_i} - x_{\min,j}^{n_i}}{x_{\max,j}^{n_i} - x_{\min,j}^{n_i}} \tag{4}$$

$x_{\max,j}^{n_i}$ $x_{\min,j}^{n_i}$ Both represents the maximum and minimum values of serial data measured by ni on sensor j respectively. The initial sample dataset after aero engines ni have been normalized by data can be formulated as:

$$\bar{X}^{n_i} = \{\bar{x}_1^{(n_i)}, \bar{x}_2^{(n_i)}, \dots, \bar{x}_{Tn_i}^{(n_i)}\} \tag{5}$$

For the training set with temporal characteristics, this paper uses the sliding window method to segment the data, and puts the segmented data set into the model for training. The specific split

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method is: set the sliding window size L.A data set split by sliding windows S(ni)represented as:

$$S^{(n_i)} = \{s_1^{(n_i)}, s_2^{(n_i)}, \ldots, s_k^{(n_i)}, \ldots, s_{T_i-L+1}^{(n_i)}\} \tag{6}$$

And $s_k^{(n_i)} = \{\overline{x}_k^{(n_i)}, \overline{x}_{k+1}^{(n_i)}, \ldots, \overline{x}_{k+L-1}^{(n_i)},\}$ .For each segmented data $s_k^{(n_i)}$,Both predicted their RUL at the last timestamp, the RUL's label set Y represented as:

$$Y = \{y^{(n_i)(m)} \mid i = 1,2,\ldots,N, m = 1,2,\ldots,T_{n_i} - L + 1\} \tag{7}$$

3 METHODOLOGY

AdaRUL consists of two parts: the search algorithm and the search space. The duty of the search algorithm is to sample the data augment strategy f , and f contains the specific temporal data augment operation, commonly called candidate operations in the automatic search algorithm and the operation parameters that apply the operation. f will be used to train a fixed architecture RUL prediction model whose predicted accuracy p for the remaining useful life is fed back to the controller for updating the controller itself. Section 2.1 of this chapter introduces the AdaRUL candidate operators, followed by Section 2.2 which defines the construction and size of the search space for engine timing data prediction, and finally, Section 2.3 summarizes the entire algorithm flow. Figure 1 shows the entire algorithm framework proposed in this chapter.

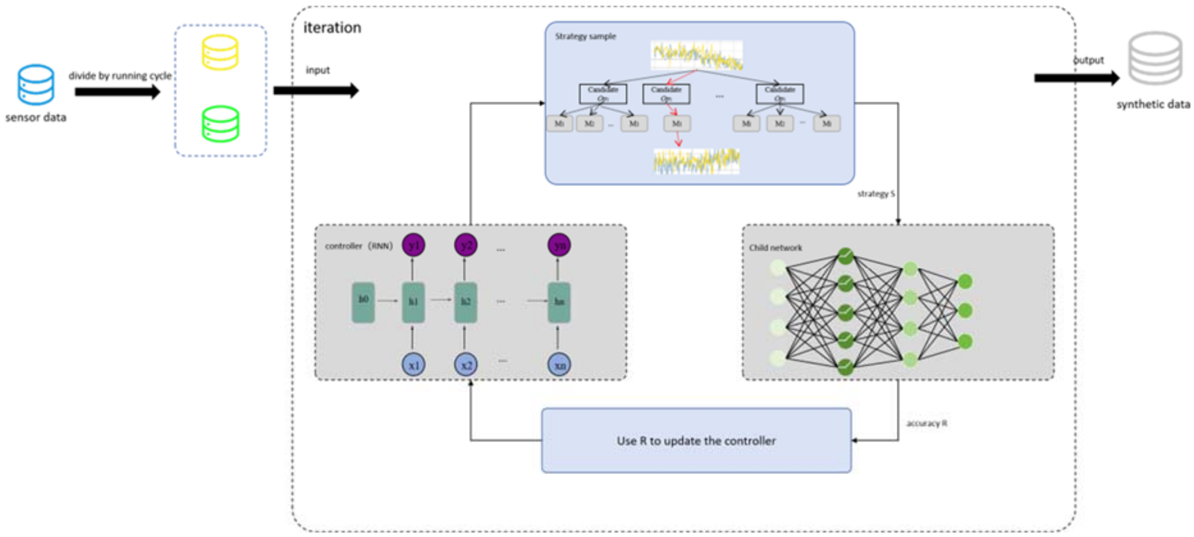

FIG.1. ADARUL OVERALL FRAMEWORK

3.1 CANDIDATE OPERATIONS

In this paper, $K = 10$ temporal data augment operations are selected to form candidate operations in the search space. These operations can be summarized simply as follows:

Time domain correlation operation - This type of operation is the generation of time series data by converting and time domain correlation on the raw data or adding random noise[18]. (e.g. slice, windows warping, Gaussian noise injection, spike)

Frequency domain correlation operation - This type of operation is the conversion of data from the time domain to the frequency domain, followed by a time domain augment algorithm to generate time series data. (e.g. amplitude adjusted Fourier transform method[19], spec Augment[20], STFT[21])

Data augment operations based on statistical generation models - Such data augment algorithms use statistical methods to simulate time series data, adding perturbations to the initial points based on the autocorrelation of the time series data, followed by subsequent data points that perturb with the perturbed data for the model generated time series data. (e.g., local and global trend methods[22], mixture autoregression models[23].)

Data Augment Method Based on Generation Countermeasures Network - Generation countermeasures network is based on the idea of game theory, learning itself from real time series data, and finally generating synthetic data with high similarity to the probability distribution of real experimental data through multiple iterations of the discriminator and generator. (e.g., currentGAN [24], timeGAN [25], multipleGAN[26])

Table 1 lists a detailed description of candidate augment operations and a selection magnitude of parameters. In the data augment strategy search, the parameters' selection magnitudes are uniformly discrete to L levels (where the relevant operations without amplitude settings are also discrete by L levels), so that in the search space, there are $K \times L$ sub strategies in common.

3.2 SEARCH SPACE

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In this section, Q denotes the search space with, K denotes the candidate number of operators, L denotes the parameter selection range of the candidate operator, and P denotes the probability of applying the candidate augment operation. One of the sub strategies S of the policy set is denoted as $c(o_k, m_l, p_i)$, which consists of a set of candidate operations $o_k \in \{o_1,...,o_K\}$ and a discrete parameter rating $m_l \in \{m_1,m_2,...,m_L\}$ and the corresponding probability of selecting one operation $p_k \in \{p_1, p_2,...p_K\}$ .Unlike the AutoAugment algorithm originally applied to image processing, this article sets the probability of all candidate augment operations to 1:

$$p_1 = p_2 = ... = p_K = 1 \tag{8}$$

A complete engine operating cycle is divided into 2 sub cycles according to the characteristics of the timing degradation characteristics of the engine: Normal operating cycle c_r and degradation cycle c_d .Considering the obvious difference of time series characteristics between normal period and degenerate period, data augment strategies are searched in time series space for each sub period. That is, in this article, when a data augment operation is performed for a complete operating cycle of an engine unit, its data augment strategy consists of data augment strategy for normal operating subcycle $c_r(o_k, m_l, p_i)$ and data augment strategy for degraded operating subcycle $c_d(o_k, m_l, p_i)$.

In summary, the sequence data $x^{(n_i)}_{1\sim Tn_i, j}$ measured by the j sensor of the N_i engine, the enhanced data generated by the selected strategy, can be represented as

$$\begin{cases} [x^{(n_i)}_{1\sim Tn_i,j}]' = \begin{bmatrix} c_r \\ c_d \end{bmatrix} \\ c_r \in \begin{bmatrix} c_r(o_1,m_1) & c_r(o_1,m_2) & ... & c_r(o_1,m_L) \\ c_r(o_2,m_1) & c_r(o_2,m_2) & ... & c_r(o_2,m_L) \\ ... & ... & ... & ... \\ c_r(o_K,m_1) & c_r(o_K,m_2) & ... & c_r(o_K,m_L) \end{bmatrix} \\ c_d \in \begin{bmatrix} c_d(o_1,m_1) & c_d(o_1,m_2) & ... & c_d(o_1,m_L) \\ c_d(o_2,m_1) & c_d(o_2,m_2) & ... & c_d(o_2,m_L) \\ ... & ... & ... & ... \\ c_d(o_K,m_1) & c_d(o_K,m_2) & ... & c_d(o_K,m_L) \end{bmatrix} \end{cases} \tag{9}$$

TABLE 1. DESCRIPTION OF THE CANDIDATE TIMING DATA AUGMENT OPERATION (AND ITS ACRONYM) AND MAGNITUDE. ("NONE" MEANS NO PARAMETERS AND THEIR VALUE MAGNITUDE FOR THE OPERATION)

Operation (acronym)	Description	Magnitude (Parameter range)
Windows Warping (WW)	Performs local distortion operations on the timeline in the time series, with amplitude representing the regular coefficient of timeline distortion	[0.1,0.9]
Gaussian noise injection (GNI)	To add noise conforming to the Gaussian distribution (normal distribution) in the raw time series data, the amplitude representing the standard deviation of the probability density function of the Gaussian distribution	[3.0, 10.0]
Spike injection (Spike)	Inserting a "spike" signal into the raw time series data to change the shape of the data, the amplitude representing the extent of the spike	[0.90, 0.99]
specAugment (sA)	Converts the time domain to the frequency domain and increases data diversity by performing simple transformations on the spectrum	null
Local and global degradation trend(L&GT)	Increasing data by adjusting or simulating local and global trends in time series data, the amplitude represents the range of slope coefficient adjustments	[-100,100]
Mixture autoregression model - 1 (MA-1)	By combining multiple autoregression models to enhance the real sample data, we choose the second order (XGBoost, Linearregression) autoregression model AR (2), where the amplitude represents the value of the first dimension in the two-dimensional vector.	[0.1,0.9]
Mixture autoregression model - 1 (MA-2)	By combining multiple autoregression models to enhance the real sample data, we choose the second order (SVR, LightGBM) autoregression model AR (2),	[0.1,0.9]

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	where the amplitude represents the value of the first dimension in the two-dimensional vector	
timeGAN (t-GAN)	Learning the distribution of data through adversary training between timeGAN's generator and discriminator	null
recurrent-GAN (r-GAN)	Same as above	null
Multiple-GAN(m-GAN)	Same as above	null

The ultimate goal of the model is to find the final data augment strategy consisting of sub strategies for the engine unit in the search space according to the specific operating conditions.

4 EXPERIMENTS

All tests were run on a computer equipped with a windows11 system and NIVIDA GeForce RTX 4070Ti Super. Build the algorithm under the framework of Pytorch and optimize the learning parameters using the Adam algorithm with an initial learning rate set to 5×10-4 and a learning rate decay factor set to 0.94. The batch size for training on four sub datasets is 32 and the sliding window length is set to $L=30$.

4.1 DATASETS

The C-MAPSS open-source aeroengine degradation trajectory dataset is used to verify and evaluate AdaRUL.Which an engine performance degradation simulation dataset provided by NASA at the PHM08 competition in 2008, contains four sub-datasets FD001, FD002, FD003, and FD004.

The dataset has 26 columns, the first of which is the engine unit number, the second is the engine's operating cycle, the second through fifth are the operating conditions, and the remaining 6-26 are the sensor measurements, of which seven sets of sensors acquired data are constant and do not vary with the engine's operating cycle time. The remaining $n_v = 14$ group of sensor acquisition data are selected in this article as algorithm inputs, 14 group of sensor input metrics described in Table 2:

TABLE 2. THE SYMBOLS AND MEANINGS OF INPUT FEATURES IN THE C-MAPSS DATASET

Serial number	Symbol	Meaning
1	T24	LP compressor exit temperature
2	T30	HP compressor exit temperature
3	T50	LP turbine exit temperature
4	P30	HP compressor outlet total pressure
5	Nf	Uncorrected fan speed
6	Nc	Uncorrected core engine rpm
7	Ps30	HP compressor exit static pressure
8	PHI	Fuel flow and P30 ratio
9	NRf	Fan corrected speed
10	NRc	Core Machine Revised RPM
11	BPR	Bypass ratio
12	htBleed	Bleed air enthalpy
13	W31	HP turbine cooling air flow
14	W32	LP turbine cooling air flow

The test set for each sub data set had more than 100 measured engine units, FD001 and FD003 for engine degradation trajectory data under a single operating condition, and FD002 and FD004 for engine degradation trajectory data under multiple operating conditions. Additionally, FD001 and FD002 are degradation data in a single engine failure mode. FD002 and FD004 are degradation data for multiple engine failure modes.

4.2 EVALUATION METRIC

Root means square error (RMSE) and delay penalty function were selected to measure the fitting accuracy of the model. RMSE measures the difference between the predicted and actual values of the model, and the calculation process is shown in Formula (10) :

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \hat{y}_t^{(i)2} - y_t^{(i)2}} \tag{10}$$

In practical applications, delayed predictions of engine functional degradation occur with more serious consequences than predicted in advance. So, when delayed predictions occur, we impose heavier penalties on the model. Based on the above description, the delay penalty function (called score in the formula) for such indicators is defined as:

$$Score = \sum_{i=1}^{N} s_i, s_i = \begin{cases} e^{-\frac{\hat{y}_t^{(i)} - y_t^{(i)}}{13}} - 1, \hat{y}_t^{(i)} - y_t^{(i)} < 0 \\ e^{\frac{\hat{y}_t^{(i)} - y_t^{(i)}}{10}} - 1, \hat{y}_t^{(i)} - y_t^{(i)} \geq 0 \end{cases} \tag{11}$$

The lower the value of the RMSE and delay penalty function, the more accurate the model's predictions are.

4.3 RESULTS OF THE GENERATED DATA

To assess AdaRUL's ability to generate simulated data, we compared the degradation trajectories of the generated data with the real data. The specific experimental design scheme is as follows: we randomly select an engine unit from FD001's data set as a training data set, allowing AdaRUL to generate simulated data based on the actual experimental data of that engine unit. Because the amount of data is too large, this article only selects the strategy cases where two of the engine units were selected from the search space when AdaRUL was running in FD001(As shown in table 3).

In the experiment, each complete time series data was divided into two sub data segments for processing, and the output of the model was also two sub sequence segments. We stitched the sub sequence segments in chronological order to get the complete analog data segment. The figure below compares the degradation trends of simulated and real data.

The blue line segments in the figure2 represent real data for the test set, and the yellow line segments represent simulated data generated by the model. Looking at the changing trend of the blue and yellow segments in the diagram, it can be concluded that AdaRUL captures the global degradation characteristics well as they change with the engine operating cycle. In addition, the overall data fluctuation range of the simulated data is in an acceptable range, i.e. no impractical data are generated, which indicates that the algorithm has some stability, which is a very important feature in data augment algorithms.

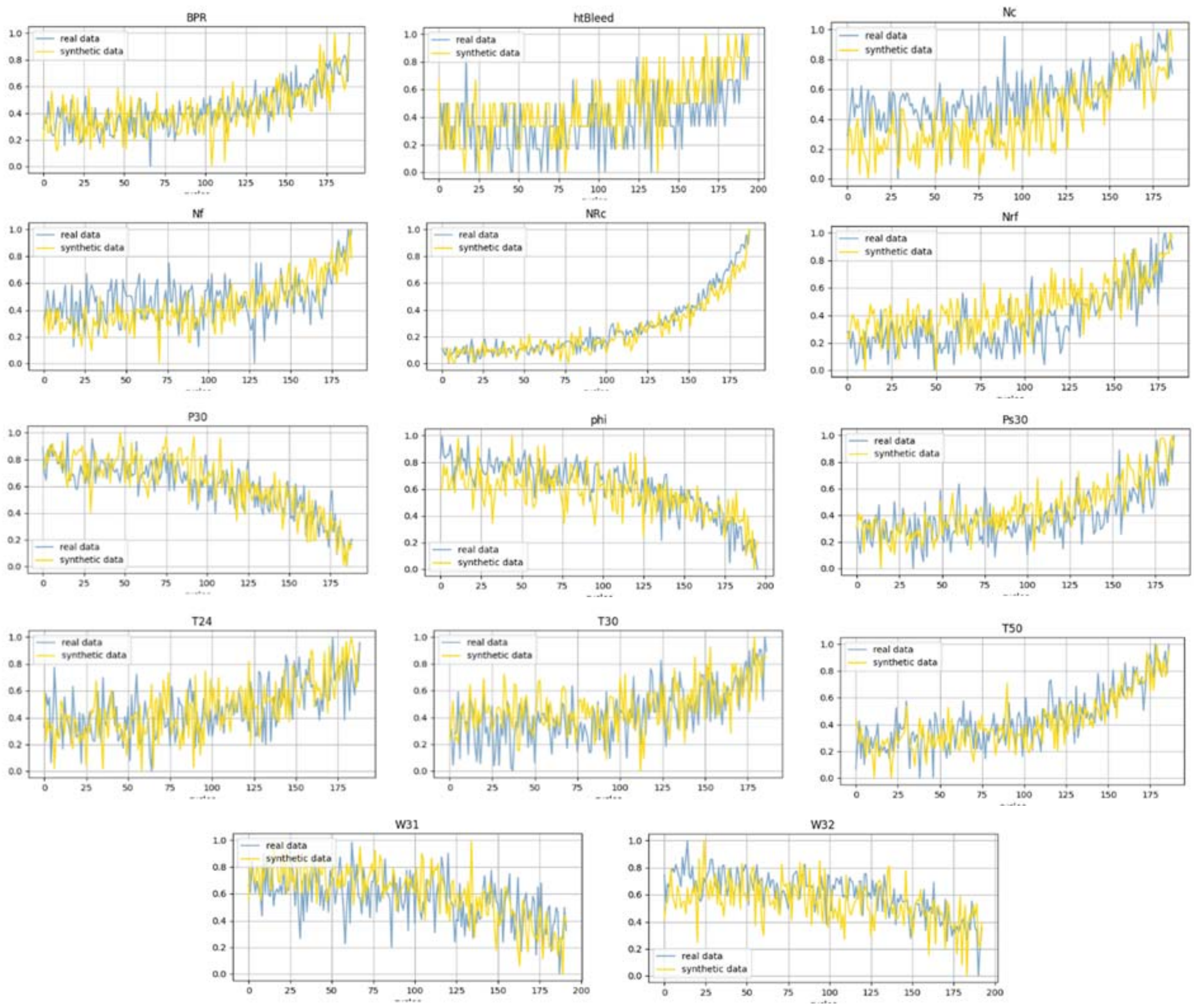

FIG. 2. COMPARISON OF DEGRADATION TRENDS OF REAL AND SIMULATED DATA IN A BROKEN LINE CHART

TABLE 3. RESULTS OF ADARUL'S PARTIAL POLICY SEARCH EXPERIMENT IN FD001 (WHERE THE SUB POLICIES ARE REPRESENTED IN THE FORMAT ['SUB POLICY ENGLISH SHORTHAND ',' MAGNITUDE RANGE'])

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Engine unit serial number	Variable	Cr	Cd
#Unit031	T24	[WW, 0.3]	[r-GAN, null]
	T30	[WW, 0.5]	[m-GAN, null]
	T50	[L&GT, 30]	[t-GAN, null]
	P30	[t-GAN, null]	[t-GAN, null]
	Nf	[MA-1, 0.2]	[r-GAN, null]
	Nc	[L&GT, 30]	[t-GAN, null]
	Ps30	[sA, null]	[spike, 0.92]
	PHI	[L&GT, 30]	[m-GAN, null]
	NRf	[WW, 0.6]	[m-GAN, null]
	NRc	[WW, 0.3]	[r-GAN, null]
	BPR	[L&GT, 40]	[sA, null]
	htBleed	[spike, 0.91]	[t-GAN, null]
	W31	[GNI, 4.0]	[t-GAN, null]
	W32	[GNI, 5.0]	[GNI, 8.0]
#Unit099	T24	[WW, 0.6]	[WW, 0.8]
	T30	[GNI, 4.0]	[m-GAN, null]
	T50	[L&GT, 70]	[t-GAN, null]
	P30	[m-GAN, null]	[m-GAN, null]
	Nf	[spike, 0.96]	[t-GAN, null]
	Nc	[WW, 0.6]	[r-GAN, null]
	Ps30	[MA-2, 0.5]	[r-GAN, null]
	PHI	[MA-1, 0.5]	[t-GAN, null]
	NRf	[WW, 0.7]	[MA-1, 0.3]
	NRc	[sA, null]	[t-GAN, null]
	BPR	[t-GAN, null]	[t-GAN, null]
	htBleed	[sA, null]	[sA, null]
	W31	[GNI, 7.0]	[m-GAN, null]
	W32	[GNI, 4.0]	[t-GAN, null]

4.4 RESULTS OF RUL PREDICTION

The ultimate purpose of data augment is to improve the fit performance of the model in the remaining service life prediction mission. To verify whether AdaRUL can effectively enhance the fitting capability of prediction models, the following comparative experiments were designed. The specific experimental protocol is described below:

Step 1: Utilize four predictive models (CNN, RNN, LightGBM, LSTM) to conduct RUL predictions for all engine units across four sub-datasets, namely FD001 to FD004, and compute the average RMSE and mean ScoreFunction for the engine units in each sub-dataset.

Step 2: AdaRUL was used to simulate the experimental data of all engine units in the four datasets FD001 to FD004, and simulation data was generated. The data volume was doubled, and the model from step 1 was used again for prediction, and RMSE and ScoreFunction were calculated.

Step 3: Use AdaRUL to generate synthetic data, triple the data size, use the model from Step 1 again for prediction, and calculate RMSE and Score.

All the above experiments were conducted on the same experimental equipment, and Table 4 records all the experimental results. From the experimental data, it can be seen that AdaRUL generated high-quality enhanced data in four scenarios: single operating condition scenario, multi operating condition scenario, single failure mode, and multi failure mode, which significantly improved the predictive ability of the baseline model. AdaRUL can not only improve engine RUL prediction under single fault mode and operating conditions, but also significantly improve engine RUL prediction performance under multiple operating conditions and diverse fault modes.

TABLE 4. COMPARISON RESULTS OF RMSE AND SCORE FOR DIFFERENT METHODS IN THE C-MAPSS DATASET

Model	RMSE				Score			
	FD 001	FD 002	FD 003	FD 004	FD 001	FD0 02	FD 003	FD0 04
CNN	18. 95	21. 03	18. 04	23. 86	502 .25	240 7.77	511 .50	487 5.52
CNN+AdaR UL	14. 19	19. 52	16. 67	21. 89	345 .33	196 2.86	374 .95	299 4.65
RNN	15. 48	18. 52	14. 77	21. 60	370 .16	204 8.45	388 .67	307 5.48

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RNN+AdaRUL	14.05	16.89	12.28	19.97	266.14	1309.49	310.52	2548.71
LightGBM	13.52	18.86	13.98	19.55	303.44	1856.62	343.45	2894.67
LightGBM+AdaRUL	12.67	16.50	12.14	17.17	201.57	1170.95	254.86	1999.02
LSTM	11.58	16.28	12.77	17.87	275.79	1515.83	300.57	2005.28
LSTM+AdaRUL	9.98	13.04	10.52	14.43	213.10	126734	233.67	1592.36

In addition, to compare the performance of AdaRUL with other data augmentation models, this paper compared AdaRUL with existing data augmentation models. The comparison results are shown in Figure 3. Figure 3 shows the RMSE and Score values of the four subsets of C-MAPSS after data augmentation using a mixed autoregressive model, timeGAN, recurrent GAN, and AdaRUL, followed by prediction using LSTM.

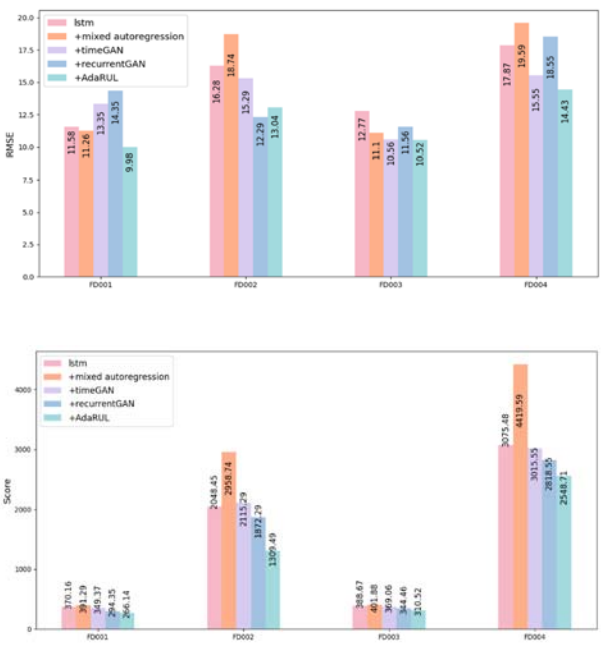

FIG. 3. BAR CHART OF C-MAPSS DATASET COMPARATIVE EXPERIMENT

From the bar chart, it can be seen that some data augmentation algorithms (such as hybrid autoregressive models) enhance the dataset under multiple operating conditions, and the resulting expanded dataset may have a certain negative impact on the prediction accuracy of the basic model. Most data augmentation models are unable to maintain consistent performance in RUL prediction tasks under multiple operating conditions. For example, for the mixed autoregressive model, the simulated data generated by the model under single operating conditions of FD001 and FD003 can effectively reduce the root mean square error of RUL prediction, while the enhancement effect on the degradation trajectory data of FD002 and FD004 under multiple operating conditions is poor. The root means square error of RUL prediction after expanding the dataset is actually higher. Due to its ability to adaptively search for the optimal strategy based on different datasets, AdaRUL maintains good consistency in the simulated data generated under four sub datasets, which has a significant effect on improving prediction accuracy.

5 CONCLUSION

This article introduces a data augmentation method, AdaRUL, based on the Autosegment automatic search strategy to enhance engine multivariate monitoring data. This method constructs a strategy search space and dynamically samples sub strategies in the search space based on the accuracy feedback of the prediction model through reinforcement learning strategies, in order to generate high-quality simulation data under different operating conditions and fault modes, and to achieve more effective assistance for deep learning models in accurately predicting the operating life of aircraft engines. The experimental results show that the synthetic data generated by the AdaRUL algorithm can accurately simulate the degradation trajectory of various monitoring data of the engine, and its sample probability distribution is close to the real dataset. Adding synthetic data to a real dataset can significantly improve the accuracy of deep learning models in predicting engine RUL.

In the future, to address the slow training process of the model, we will further streamline the search space and reduce the time cost required for training the model; In addition, in practical applications, sensors often output measurement data with many missing values, resulting in incomplete training datasets that are difficult to train. The focus will be on the application research of AdaRUL in this direction in the future.

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