Improved Condition Monitoring of Aircraft Auxiliary Power Unit Based on Transfer Learning

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***Abstract*—The status of aircraft auxiliary power unit (APU) has direct influence on the safety and reliability of the aircraft. However, only a few on-wing sensors can bring valuable information for condition monitoring, which are not sufficient for formulating effective monitoring model. In this study, one approach is proposed to improve the condition monitoring of the aircraft APU based on transfer learning, which utilizes the abundant simulation data for training the condition monitoring model. It is expected that the feature of simulation data can help to improve APU monitoring result. To verify the effectiveness of this proposed approach, the real data from China Southern Airlines Company Limited Shenyang Maintenance Base and the simulation data from NASA Ames Research Center are utilized.**

Keywords-auxiliary power unit; transfer learning; condition monitoring; remaining useful life prediction

I. INTRODUCTION

Safety has always been a primary issue in the field of aviation. Aircraft auxiliary power unit (APU), as the auxiliary power of aircraft, also needs to work in high reliability. However, components of APU (e.g., combustors, shafts, and blades) work at harsh environment and long hour operation. When the APU is operating, the internal temperature and pressure of APU are extremely high. Such harsh environment may result in faults of the APU (e.g., wear, crack, and distortion) [1]. These factors and the complex structure bring a huge challenge to monitor APU condition.

There are two typical methods to conduct the condition monitoring. The first one is based on model and the second one is based on data-driven model [2]. Since APU is such a complex system that it is quite difficult to formulate an accurate model [3-4]. In contrast, the data-driven method can be carried out with the available sensor data [5-6]. With the improvement of sensor technology and the enrichment of sensor types, more and richer sensor data can be obtained. Better data analysis results can be obtained by means of sensor data. Thus, the data-driven approach has become appropriate technology for the complex system condition monitoring. But, how to utilize the available sensor data is difficult.

Some studies have been carried out to choose the most suitable data from sensors for APU condition monitoring. Liu et al. [7] put forward one way of sensor selection via the improved permutation entropy to implement aero-engine condition monitoring. Compared with the works in [8-9], which utilize observing method to select sensor data for condition monitoring method, the improved permutation entropy method can reach more precise and stable results. In [10], one kind of monotonous trend measurement method in sensor data is proposed to select relatively optimal input for condition monitoring. The selection of different sensor data realized by mutual information and the influence on condition monitoring are comprehensively studied [11].

In the aforementioned studies, the proposed approaches are assessed by the simulation data set. Based on the on-wing sensor data of exhaust gas temperature (EGT), Cheng et al. [12] fuse ensemble empirical mode decomposition and Gaussian process regression (GPR) to realize the condition monitoring. Based on this work, Liu et al. [13] propose the combination of EGT and other on-wing sensor data to improve the monitoring results. However, these works omit that the different sources of sensor data may be able to help enhance the condition monitoring result, e.g., the available simulation data of the same kind APU.

In this work, one kind of transfer learning is proposed to realize the condition monitoring of the on-wing APU. Transfer learning aims to bridge the gap between the training data and test data. Generally, the training data and test data have different feature space and distribution [14]. To realize what to transfer and how to transfer, the proposed approach utilizes the simulation data and real data of APU together to train the transfer learning model, and adopts the real sensor data as the test data.

For the same kind of turbine gas APU, the training data are provided by NASA Ames Research Center and the test data are provided by China Southern Airlines Company Limited Shenyang Maintenance Base (SYMOB). The obtained feature from the simulation data will be transferred to the real APU condition monitoring. The methodology of GPR [5, 7, 10, 11, 13], which has been utilized widely for condition monitoring, is used to evaluate the transferred feature for predicting the condition of the target APU.

Due to the important role of APU in the aircraft, it is extremely meaningful if the condition monitoring result is improved. The small progress can bring huge benefit for enhancing the safety. Besides, the improvement is also benefit for maintenance, which can be benefit for optimizing maintenance plan and reduce maintenance base.

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II. METHODOLGY

In this section, the proposed approach will be introduced in detail. The utilized theories and metrics are illustrated.

A. *The Proposed Method*

By transferring the simulation data of APU to the on-wing application, the proposed approach is conducted to realize the condition monitoring of APU, as shown in Fig. 1.

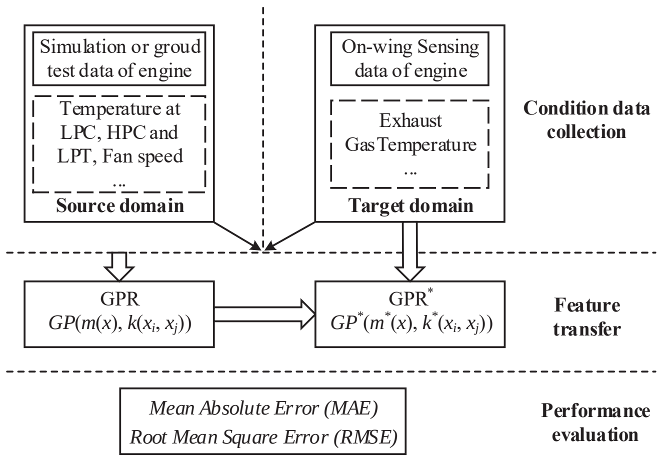

Figure 1. The proposed method based on transfer learning.

In the source domain, the simulation data of the APU are taken as the training data. GPR is applied as the condition monitoring method, which has been verified in many researches, as introduced in Section 1. The GPR model of $GP(m(x),k(x_i,x_j))$ is trained by the simulation data, which has available multi-dimensional input to train the model. As illustrated in Fig. 1, there are several kinds of temperature and pressure parameters which can help formulate the model. The detailed reference can be found in [7], which utilize seven sensors data to realize condition monitoring of the APU.

In the target domain, the test data are utilized partially to optimize the trained model. The GPR parameters are further improved to adapt the sensor data in the target domain, which are the real sensor data from the on-wing APU. As introduced in [13], one-dimensional sensor data and two-dimensional sensor data are utilized to formulate the GPR model.

Based on the utilizing sensor data from source domain and target domain, the improved $GP^*(m^*(x),k^*(x_i,x_j))$ model is expected to enhance the on-wing APU condition monitoring. The results are evaluated by two well-known metrics for precise and stable measurement, they are explained in the third part of this section.

B. *Gaussian Process Regression*

Gaussian Process has been applied in many engineering field, which is part of stochastic process. For given $\mathbf{D}=\{x_n\}_{n=1}^{N}$, $x\in R^d$, the corresponding $f(x_1),...,f(x_N)$ represent a group of random variables, which follow the joint Gaussian distribution. In this way, the group of $f(x_1),...,f(x_N)$ can be expressed by

$$f(x)\sim GP(m(x),k(x_i,x_j)), \tag{1}$$

$$m(x)=E\left[f(x)\right], \tag{2}$$

$$k\left(x_i,x_j\right)=E\Big[\big(f(x_i)-m(x_j)\big)\big(f(x_i)-m(x_j)\big)\Big], \tag{3}$$

where $k\left(x_i,x_j\right)$ sates the covariance function, and $m(x)$ represents the mean function.

For the typical application, $f(x)$ contains the noise and can be written by

$$y=f(x)+\varepsilon\,. \tag{4}$$

where $\varepsilon\in N\left(0,\sigma_n^2\right)$ represents the white noise. For the adopted $f(x)$, the observation y also complies with the Gaussian Process and can be given by

$$y\sim GP\left(m(x),k(x_i,x_j+\sigma_n^2\delta_{ij})\right), \tag{5}$$

where δ_{ij} denotes the Dirac function.

In the following step, the training data are supposed to be $\mathbf{D}_1=\{x_i,y_i\}_{i=1}^{N}$ and the test data are supposed to be $\mathbf{D}_2=\left\{x_i^*,y_i\right\}_{i=1}^{N}$, where $x_i,x_i^*\in R^d$, in which d denotes the dimension of input data. m and m^* are the mean vectors. The $f(x^*)$ represents the output by using the test data and y represents the training data. By utilizing (5), y^* and y comply with the Gauss joint distribution, the according equation is expressed by

$$\begin{pmatrix} y \\ y^* \end{pmatrix}\sim\left(\begin{bmatrix} m \\ m^* \end{bmatrix},\begin{pmatrix} C(X,X) & K(X,X^*) \\ C(X^*,X) & K(X^*,X^*) \end{pmatrix}\right). \tag{6}$$

where $C(\bullet)$ refers to the covariance matrix of the data and it is denoted as $C(\bullet)=K(\bullet)+\delta_{ij}I$, in which δ_{ij} is the white noise and $I\in R^{N\times N}$ is the unit matrix. X and X^* denote the matric of training and test data, respectively. In addition, the covariance of the data can be presented by $K(\bullet)$. In this way, posterior conditional distribution of y^* can be obtained by

$$y^*|X,y,X\sim N\left(\overline{y^*},\mathrm{cov}(y^*)\right), \tag{7}$$

$$\overline{y^*}=E\left[y^*\middle|X,y,X^*\right]=m+K(X^*,X)C(X,X)^{-1}(y-m), \quad (8)$$

$$\mathrm{cov}(y^*)=K(X^*,X^*)-C(X,X)^{-1}K(X,X^*). \quad (9)$$

Based on (8) and (9), the predicted condition results can be obtained by

$$\bar{y}(x^*)=m(x^*)+(k^*)^T C^{-1}\left(y-m(x)\right), \quad (10)$$

$$\sigma_f^2(x^*)=k(X^*,X^*)-(k^*)^T C^{-1}k^*. \quad (11)$$

The related parameters in these two equations have been introduced in the aforementioned explanation. During the explicit model formulation, the sensor data of the APU are utilized to train this model. Then, the trained model can utilize the new input to predict the condition of the APU.

C. Metrics for Condition Monitoring

To evaluate the condition monitoring results, two evaluation metrics are adopted. They are utilized to measure the accuracy and stability of monitoring result, respectively. The definitions of these two metrics are given in the following two equations.

$$MAE=\frac{1}{N}\sum_{k=1}^{N}\left|P_k-R_k\right|, \quad (12)$$

$$RMSE=\sqrt{\frac{\sum_{k=1}^{N}\left(P_k-R_k\right)^2}{N}}. \quad (13)$$

In (12) and (13), P_k denotes the predicted results, R_k represents the actual value, and N is the number of predicted cycle. The smaller MAE and $RMSE$ values represent the better performance of accuracy and stability.

III. EXPERIMENTAL RESULTS AND DISCUSSION

This section describes the data used in this article in detail. The comparison between the proposed method and the existing method is implemented and discussed.

A. DATA DESCRIPTION

To implement the transfer learning, the APU condition monitoring data provided by PHM 2008 Conference are utilized as the source data [15]. In the data set, the condition of aircraft gas turbine engine can be reflected by many dimensional sensing data. The structure of the gas turbine is shown in Fig. 2.

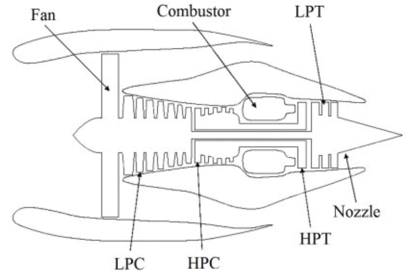

Figure 2. The simulated aircraft engine structure [16].

The Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) is used to simulate the working process of gas engine, and it can simulate the real working condition. Both open and closed loop simulation are optional to the user. The connections between the different subsystems are shown in Fig. 3.

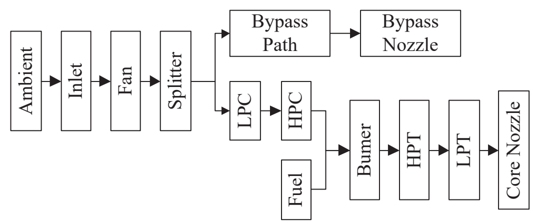

Figure 3. Layout of subsystems in the aircraft engine [16].

The engine control system is built inside of the engine, which is consisted of three parts. They are fan speed controller, several regulators and limiter, respectively. The limiters are utilized to make sure that the engine operates within the approved manipulation limitations. The simulation conditions can be set and the simulation environments are the same as the practical scenario. To acquire the engine condition, 21 sensors are employed to collect the engine condition, which are described in Table I

TABLE I. SENSORS EMPLOYED IN THE SIMULATION [16].

Index	Symbol	Description	Units
1	T2	Total temperature at fan inlet	°R
2	T24	Total temperature at LPC	°R
3	T30	Total temperature at HPC	°R
4	T50	Total temperature at LPT	°R
5	P2	Pressure at fan inlet	psia
6	P15	Total pressure in bypass-duct	psia
7	P30	Total pressure HPC outlet	psia
8	Nf	Physical fan speed	rpm
9	Nc	Physical core speed	rpm
10	Epr	Engine Pressure ratio	-
11	Ps30	Static pressure at HPC outlet	psia
12	Phi	Ratio of fuel flow to Ps30	pps/psi
13	NRf	Corrected fan speed	rpm
14	NRc	Corrected core speed	rpm
15	BPR	Bypass ratio	-
16	farB	Burner fuel-air ratio	-
17	htBleed	Bleed enthalpy	-
18	Nf_dmd	Demanded fan speed	rpm
19	PCNfR_dmd	Demanded corrected fan speed	rpm
20	W31	HPT coolant bleed	lbm/s
21	W32	LPT coolant bleed	lbm/s

ºR The Rankine temperature scale
psia Pounds per square inch absolute
rpm Revolutions per minute
pps Pulse per second
psi Pounds per square inch
lbm/s Pound mass per second

The test data come from the real on-wing sensor data of the aircraft gas turbine engine, which are provided by SYMOB. These data are transmitted to the data center of airlines through the aircraft communications addressing and reporting system (ACARS). In ACARS report, A13 message contains the self-starting information of engine. There are 11 segments in the A13 message, including CC, $C1$, CE, $E1$, $N1$, $S1$, $N2$, $S2$, $N3$, $S3$ and V1. Each segment is consisted of several specific parameters. The parameters in $N1$, $S1$, $N2$, and $S2$ represent the operating condition of engine. Among which, the temperature and pressure are two typical monitoring parameters.

Therefore, the available parameters for implementing the condition analysis are limited. As illustrated in [13], the EGT, the combination of EGT and the bleed air pressure (BAP) are set to be the target data, respectively. To verify the effectiveness of the proposed approach, the aforementioned source data and target data will be utilized.

B. Comparison Experiments and Analysis

The comparison experiments are implemented between the results in [13] and the proposed method in this study. The target of the experiments is to predict the remaining useful life (RUL). To achieve this goal, EGT, the combination of EGT and BAP are utilized. For the following comparison analysis, the results of these two experiments are given in Fig. 4 and Fig. 5 [13]. The illustrated results in two figures have been adjusted to be relatively optimal under different length of training data and test data.

The values of *MAE* and *RMSE* in Fig. 4 are obtained as following.

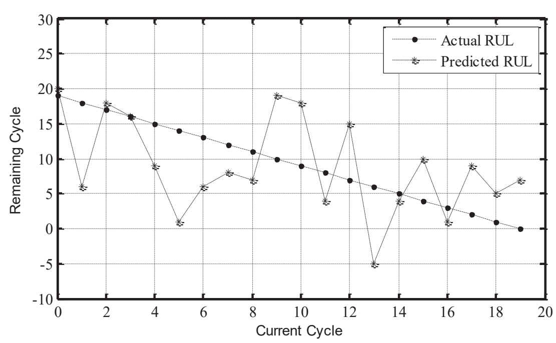

Figure 4. Experimental results only using real EGT data.

The values of *MAE* and *RMSE* in Fig. 5 are shown as following.

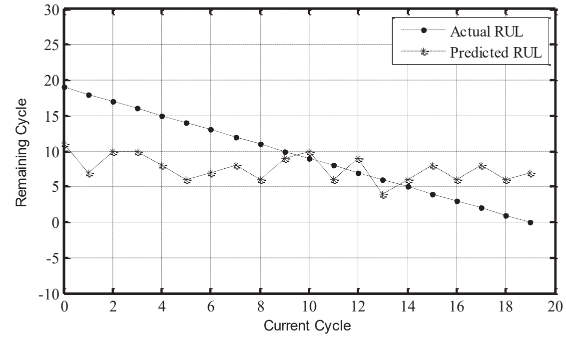

Figure 5. Experimental results only using real EGT and BAP data.

For the same sensor data in the target domain, the proposed transfer learning method utilizes the NASA simulation data as training data firstly, i.e., the source domain data. In the first comparison experiment, the partial EGT in the target domain is adopted to further improve the trained GPR model by the seven sensors data of the source domain. To be specific, 11 sensor data samples are utilized. Then, experimental results of RUL prediction are achieved, as shown in Fig. 6.

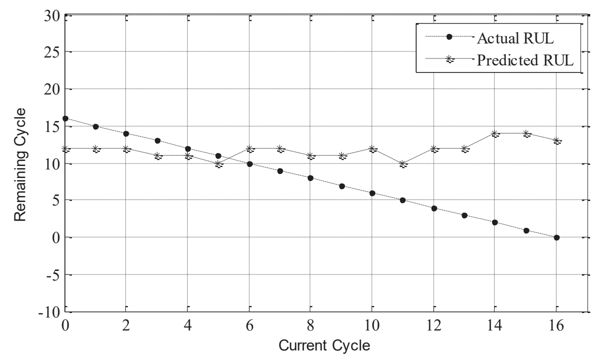

Figure 6. Experimental results using simulation data and real EGT data.

In Fig. 6, the actual RUL of the APU is represented by the dot line, the predicted RUL of the APU is represented by the star line. With the actual RUL reaching the minimum value (i.e., 0 cycle), the deviation between the predicted value and the actual value becomes larger. To measure this experimental result, the numerical values of two metrics are shown as following.

$$MAE = 5.35$$

$$RMSE = 6.69$$

Experimental results in Fig. 4 and Fig. 6 both utilize only EGT as the input of condition monitoring method. *MAE* value is reduced from 5.80 cycle to 5.35 cycle and *RMSE* value is reduced from 6.89 cycle to 6.69 cycle. Comparing these two prediction results, we can obtain that better precise and stable performance can be gained via the proposed method. Then, the second comparison experiment implemented by utilizing EGT and BAP is carried out. The experimental setting is same with the first experiment. The condition monitoring result is shown in Fig. 7.

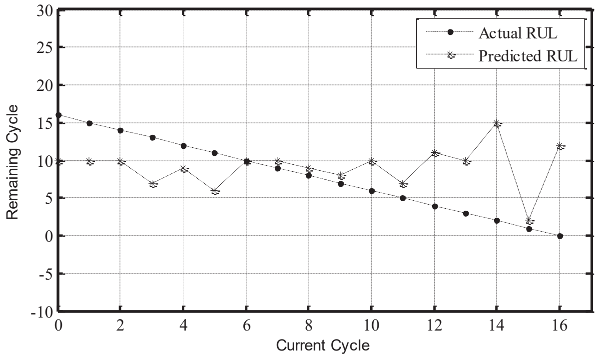

Figure 7. Experimental results using simulation data, real EGT and BAP data.

The meaning of dot line and the star curve Fig. 7 are the same as in Fig. 6. The numerical values of two metrics are shown as following:

Comparing the results in Fig. 5 and Fig. 7, which have the same experiment setting, the proposed method has better precision performance. *MAE* value is reduced from 4.80 cycle to 4.59 cycle. The aforementioned four experiment results are shown in Table 2.

TABLE II. TABLE TYPE STYLES

Experiment	*MAE*	*RMSE*
EGT without transfer learning	5.80	6.89
EGT with transfer learning	5.35	6.69
EGT and BAP without transfer learning	4.80	5.52
EGT and BAP with transfer learning	4.59	5.85

In the comparison experiments, there are four numerical values, which include two *MAE* and two *RMSE*. Besides three values of metrics enhanced by transfer learning, *RMSE* of the fourth experiment is larger than the result of EGT and BAP without transfer learning. The reason may be due to the inherent influence of GPR method when it is utilized to realize condition monitoring. Only one metric is not improved, it does not indicate that the proposed method is not valuable.

To summarize the above experiments, the feasibility of APU condition monitoring method based on transfer learning has been evaluated. Although the improvement of condition monitoring results is relatively small, it is benefit for the critical application (e.g., the aircraft fleet operation and condition-based maintenance), as illustrated in [17]. Take the China Southern Airlines Company as an example, this improvement is meaningful for the operation and maintenance of aircrafts fleet, which is comprised of hundreds of aircrafts.

IV. CONCLUSION AND FUTURE WORK

This article presents a new method in the field of APU monitoring based on transfer learning. Compared with the existing method which only relies on the on-wing sensor data, the proposed method can achieve more precise and stable results. It is expected to enhance the on-wing APU condition monitoring and bring benefit for the airlines company.

In the future, two works will be conducted. The first is to extract some potential features from the simulation data to support on-wing application. The second is to utilize the sensor data of ground cell test to formulate the on-wing monitoring model. These two works will be implemented under the framework of transfer learning.

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