A Highly Accurate Method for Forecasting Aero-Engine Vibration Levels Based on an Enhanced ConvNeXt Model

DIAN KUANG¹, YUYOU ZHAN², YAN TAN³, YI GOU², AND WENQING WU²
¹Engineering Techniques Training Center, Civil Aviation Flight University of China, Guanghan 618300, China
²College of Aeronautical Engineering, Civil Aviation Flight University of China, Guanghan 618300, China
³Aero-Engine Center, Civil Aviation Flight University of China, Guanghan 618300, China

Corresponding author: Yuyou Zhan (zyyskma@163.com)

This work was supported in part by the Civil Aviation Flight University of China through the Youth Fund under Grant Q2019-056, and in part by the Fundamental Research Funds for the Central Universities under Grant J2022-014.

ABSTRACT Vibrations are like the heartbeat of an aero-engine. In order to better understand the pulse pattern of aero-engines, we must look deep into its nature. Instead of choosing mature themes for research such as bearing vibration fault diagnosis and fault classification, this paper creatively explores vibration forecast, a subject that is hardly ever brought up in the aero-engine field. Meanwhile, an enhanced ConvNeXt model using a sliding window mechanism, which is a highly accurate forecasting method, is proposed. On the basis of using real flight datasets gathered by aircraft acquisition systems, this powerful method can track and forecast the vibration of aero-engines very precisely in a specific condition. Due to the complexity of aero-engine vibration, our method uses the sliding window to add future information on non-target parameters in order to increase the prediction accuracy of the target parameters. In some cases, forecasted values are almost identical to true values. The application of this innovative method on various vibration parameters has also been tested, in addition to its applicability to various types of aero-engines being confirmed. Finally, experiments on noise immunity and several aero-engine states involving the transition state and the steady state are conducted to strengthen the plausibility and credibility of our theories.

INDEX TERMS Aero-engine, vibration, vibration forecast, data driven, deep learning.

I. INTRODUCTION
In civil aviation, aero-engine stability and safety are regarded as extremely important aspects that guarantee a safe flight throughout the aircraft system. Due to increasing duty cycles, the performance of aero-engines will inevitably deteriorate [1]. Because of malfunctions in aero-engines involving being aged, corrosion and erosion in gas paths, blades worn out, and falling off between components, this situation might result in serious vibration accidents [2], [3]. However, current techniques for diagnosing or detecting aero-engine faults indicate that a high degree of accuracy could not be achieved due to human factors [4], [5]. The complexity of aero-engines and the secrecy principle also make it difficult for airlines and non-OEM (Original Equipment Manufacturer) companies to fully understand the operating logic of vibration systems [6], [7]. Therefore, understanding how to forecast aero-engine vibration levels accurately is extremely vital for researchers to explore the change law of aero-engine vibration. And the feedback of forecasting vibration levels will promote a huge leap in the field of aviation.

Previous studies have concentrated mainly on vibration characteristics analysis using some very professional and complicated methods [8], [9], [10]. In order to satisfy the demands of quick modeling and actual conditions, some researchers make use of AI (Artificial Intelligence) technology. However, due to the complexity of vibration systems, they prioritized fault diagnosis above forecasts and concentrated on a single vibration parameter, ignoring other essential and latent parameters [11], [12], [13]. Based on the
previous background, a proposal of a highly accurate method to forecast aero-engine vibration levels will give a significant amount of support for aero-engine design optimization and airworthiness safety monitoring. Additionally, the application scope and significance of the conclusion will be significantly impacted by the data source.

Actual flight data captured by the sensors and simulation data are the two main dataset sources. While the simulation data could not fully adapt to the vibration signal setting [14], [15], the research on aero-engines makes extensive use of it. And this raises the question of whether the experimental findings are trustworthy and useful. The actual flight datasets generated from flights can solve the above problems.

In this paper, an enhanced ConvNeXt model with the sliding window mechanism based on real flight datasets is proposed. This highly accurate method is based on the realistic background indicated above, which involves the research value, and certain challenges existing in the current relevant research are demonstrated. Figure 1 presents a part of our work.

![Figure 1](image_url)

**FIGURE 1.** The forecasting result of parts of our work (Vibration levels of low pressure turbine, Type A aero-engine).

Figure 1 clearly presents the forecasting result of vibration levels of low pressure turbine in Type A aero-engine. As can be seen, our method accurately forecasts the trend of vibration in the future and tracks its change through time.

Reviewing the topic, a new methodology is proposed for the possibility of the aero-engine vibration forecast at a highly accurate level based on the real flight dataset and multi-parameters fusion. To verify the effectiveness of this method, the prediction of different types of aero-engines is also tested. In addition, experiments on several aero-engine states involving the transition state and the steady state are conducted to strengthen the plausibility and credibility of our theories. Finally, the datasets used in this article are generated by aircraft acquisition systems, which means the result that the model forecasts could be more fit for actual flight situations.

**II. DATA PREPROCESSING**

**A. DATA SOURCE**

In order to better adapt our experimental results to actual flight situations, datasets collected by aircraft data acquisition systems are used throughout our whole study due to their advantages like ample and detailed parameters, continuous storage, easy export and processing [16]. Hence, the disadvantages of simulation and open-source datasets as unreal, single parameters, and satisfying only specific conditions are eliminated. It should be noted that the vibration level studied in this article is the data processed by the airborne vibration computer, and the computer itself will first filter out the irrelevant signal. Therefore, the vibration parameters recorded by the aircraft data acquisition system cannot obtain the frequency distribution of vibration, and only the vibration of the whole aero-engine rotor could be accessible. Hence, the forecasting target value obtained in this paper is the vibration level processed by the airborne vibration computer. Although it is unavailable to gather further information on vibration, such as modal distribution and response position, it also has certain practical significance and research value in aero-engines early warning, the design and research of aero-engines through the forecasting and tracking of sudden and common changes and large fluctuations of vibration. In addition, the study of vibration systems in other domains could also be inspired by our research.

More importantly, The operation conditions of aero-engines are divided into transition state and steady state, which involve a whole flight. Therefore, the aircraft acquisition system not only records the entire flight process but also includes these two aero-engine operating states. As a result, datasets from both states will be randomly extracted and input into our model at the same time. When the model is sufficiently complex, it could learn the patterns of these two states in training tasks and identify which state it is according to the input data during the forecasting process. Therefore, the trained model can be regarded as a general forecast model that does not need to distinguish aero-engine conditions in the data preprocessing part due to its automatic recognition capability. Meanwhile, the types of aero-engines we studied are dual-rotor turbofan engines, hence the datasets belong to the dual-rotor turbofan engine, not to others. In addition, the characteristic of any engine is different from the others after a period of service, even if they are the same type. And that will be a big problem for future practical industrial applications. In order to minimize the impact of this problem and strengthen our methodology, the data we gathered is from the aero-engine operation data of many different aircraft and different flights. As a result, the dataset we used is very comprehensive and includes as many aero-engine situations as is practical. Additionally, it significantly increases the robustness of our results.

Based on the above, there is a reason to believe that if airlines are able to fully utilize their immeasurable flight data, this will have real implications in the future. Then, our predictive model will develop into a more reliable, comprehensive, and steady one.

**B. RANDOM SAMPLING**

In this paper, random sampling is a greatly essential step for our model to learn the fit function as well as possible.
This method will randomly sample continuous steps as one batch for input, and the output will be the vibration level values in the next continued steps. And the term ‘step’ has been used to refer to situations in which time series data are used. In the current research, the step is defined as the frequency of actual flight data recording. It should be noted that one step can be representative of the sensor acquisition rate which is 1 Hz in our study. The learning algorithm could learn features, in the high dimension, and the latent representation of the changing trend of vibration better and more correctly. Because of this technique, the interaction of parameters at a certain time may also be available for the model. During the training process using this idea, the deep learning model would focus on the interaction of parameters and the changing tendency of vibration rather than on the temporal relation of flight segments. Aero-engine transition state and steady state data samples must be randomly input into the model using this method of data extraction. When the model is fairly complicated, our model may simultaneously learn the key characteristics of both states and distinguish between them based on input data in a real-world running environment.

C. PARAMETER SELECTION

In this paper, datasets come from two aero-engines with completely different types. But we try our best to pursue selecting the same parameter. When selecting parameters, the interaction of parameters and the technology principle of aero-engines will be involved. Furthermore, this essay makes reference to earlier works and expert technical manuals on aero-engines [17], [18]. Therefore, the following parameters presented in Table 1 will be chosen from the type A aero-engine. The vibration level of low pressure compressor and the vibration level of low pressure turbine will be chosen as our target parameters. The aircraft data acquisition system is a little different, while the selection of essential parameters of Type B aero-engines will do its best to remain the same.

III. METHOD

In this section, some classic and advanced learning algorithms (ResNet18, SENet18, and original ConvNeXt18) are used for comparison. To accomplish some goals, such as quick modeling to evaluate the theory and fit the size of the dataset, light models will be chosen. Figure 2 presents the overall scheme of our proposed method.

A. THE SLIDING WINDOW MECHANISM

Throughout the whole running term of the aero-engine, its levels will experience abrupt, significant variations. This phenomenon may be caused by the transmission of the control signal into the controlled system, resulting in the change of the controlled system. This sudden change will be reflected in the changes in various parameters. However, when our model is processing common prediction tasks, it not only predicts the target value but also predicts the future trend of other parameters at the same time. In this process, the model will think along with the changing trend of input parameters (like 100 steps/HZ/second). Thus, it becomes an inertial system, and cannot give feedback to the sudden change of parameters in time. Meanwhile, If the sudden change factor is not in the input data but in the time span (like 10 steps/HZ/second) of the forecast data, a large difference might occur between the output value and the actual value. For instance, the aero-engine is going to shift into the transition state. As a result, an effective method should be adopted to address this problem brought by the state change.

To break these obstacles, a special strategy called the Sliding Window Algorithm will be utilized. The term ‘Sliding Window Algorithm’ has been used to refer to situations in which the network communication in the field of computer network (Transfer Control Protocol) [19]. Figure 3 shows the architecture of our idea. Whenever a forecast value is calculated, the window takes a step forward. And take the latest

| Parameter                                | Unit  |
|------------------------------------------|-------|
| Vibration levels of low pressure compressor | MILS.DA |
| Vibration levels of high pressure compressor | MILS.DA |
| Vibration levels of low pressure turbine  | MILS.DA |
| Vibration levels of high pressure turbine | MILS.DA |
| High pressure compressor outlet pressure (PS3) | PSIA |
| Total air temperature (TAT)              | °C    |
| High pressure compressor inlet temperature (T25) | °C |
| High pressure compressor outlet temperature (T3) | °C |
| Low pressure rotor speed (N1)            | %RPM  |
| High pressure rotor speed (N2)           | %RPM  |

For another type of aero-engine, the parameters that we chose from the type B aero-engine are shown in Table 2. The vibration level of low pressure compressor and the vibration level of high pressure compressor will be chosen as our target parameters. The aircraft data acquisition system is a little different, while the selection of essential parameters of Type B aero-engines will do its best to remain the same.

TABLE 2. Parameters selection (Type B).

| Parameter                                | Unit  |
|------------------------------------------|-------|
| Vibration levels of low pressure compressor | MILS.DA |
| Vibration levels of high pressure compressor | MILS.DA |
| Vibration levels of low pressure turbine  | MILS.DA |
| Vibration levels of high pressure turbine | MILS.DA |
| High pressure compressor outlet pressure (PS3) | PSIA |
| Fan inlet temperature (T12)              | °C    |
| High pressure compressor inlet temperature (T25) | °C |
| High pressure compressor outlet temperature (T3) | °C |
| Low pressure rotor speed (N1)            | %RPM  |
| High pressure rotor speed (N2)           | %RPM  |
output predictive value as the latest value of target parameters in the next step which needs the model to predict. And other non-target parameters are still gathered from sensors. When the forecast process is done, we just need to calculate MSE between true values and predictive values. Therefore, future information (latently sudden change) on other impact factors (like state changes) will be taken into consideration based on this series of operations when the model is computing. Based on this idea, erroneous information can be corrected during the forecast process. As a result, this technology can be used...
not only for the early warning of the large error in a single step but also to count the accumulated multistep error.

### B. Squeeze-And-Excitation Network

After He [20] et al proposed the classic neural network, Residual Network (ResNet), this architecture has had a great impact on the computer vision (CV) field and continues to this day. The structure of this model is shown in Figure 4. This network learns the residual $F(x)$ between $H(x)$ and $X$, not directly obtaining the expectation function. By learning the residual to reach the optimal function step by step, the model with the smallest error can be obtained.

![Figure 4. The architecture of a residual block.](image)

Under the tide of Transformer sweeping the field of deep learning, the ConvNeXt model [21] which is based on a ResNet proposed by FAIR has achieved the same effect as the Swin Transformer [22]. This finding shows that the ResNet still has a large potential. Based on the residual idea, it improves the model’s structure, makes the overall structure more excellent and reasonable, and updates and modernizes associated components. And since the ViT model introduced the Transformer structure into CV, the following MAE model and Swin Transformer model are derived and developed on this basis. The most important step of the ViT model is to divide the image into patches, that is, different regions, and process them in patches [23]. The traditional ResNet model uses a $7 \times 7$ convolutional layer maximum pooling layer to directly process the image as a whole. And the ConvNeXt model adopts this kind of idea. It first processes the input with a $4 \times 4$ convolutional layer and processes the information of one patch at a time. Therefore, it effectively reduces the downsampling times and improves the model performance. Additionally, the network width is improved by increasing the number of channels from 64 to 96. The processing of one channel by each convolutional kernel is independent of the other channels, just like the self-attention mechanism. One channel contains mixed weighted spatial information. In addition, the residual module is changed as shown in Figure 5, so that information loss caused by compressed dimensions can be avoided when converting information between feature spaces of different dimensions. Finally, some small modules are modernized, such as replacing ReLU with GELU and reducing the number of active layers.

To improve the performance of the ConvNeXt model, a SE (Squeeze-and-excitation) block [24] which was the champion of the last ImageNet 2017 competition will be added to the ConvNeXt model. Figure 6 shows its structure. This global architecture based on a residual block ensures the model’s excellent performance. Through Squeeze and Excitation techniques (See Formula 1 and Formula 2), these two ideas explicitly model channel interdependencies within modules.

$$F_{sq}(u_c) = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} u_c(i,j), \quad z \in R^C$$  \hspace{1cm} (1)

$$F_{ex}(z, W) = \sigma(W_2 \text{ReLU}(W_1 z))$$

\[ W_1 \in R^{\frac{C}{r}\times C}, \quad W_2 \in R^{C\times \frac{C}{r}} \]  \hspace{1cm} (2)

![Figure 6. The structure of a SE-ResNet module.](image)
Furthermore, a strategy called “Feature recalibration” looks like an attention mechanism in a sense, which means the block automatically acquires the importance of each feature channel via learning, and then improves the useful features according to this importance and suppresses the features that are not useful for the current task. To meet our research goal, we have slightly modified these models to better match our study.

**C. OPTIMIZER AND LEARNING RATE CONTROL STRATEGY**

The optimizer we used in this study is Adaptive Moment Estimation with decoupled weight decay (AdamW)[25]. Hyperparameters $\beta_1, \beta_2$ and Weight Decay are set as 0.9, 0.999 and 0.05 for all training tasks. In order to make our model learning better, The control strategy of learning rate is Cosine Annealing LR. And according to Formula 3. Its change law during training is shown in Figure 7. The meaning of these parameters will be presented in Table 3. Hyperparameter $T_{\text{max}}$ is equal to training epochs when the model is in the training tasks.

$$\eta = \eta_{\text{min}} + 0.5 \times (\eta_{\text{max}} - \eta_{\text{min}}) \times (1 + \cos \left(\frac{T_{\text{cur}}}{T_{\text{i}}}\right))$$

**IV. METHOD VALIDATION**

In our experiments section, low pressure compressor vibration and low pressure turbine vibration in the Type A aero-engine will be used to test the viability of high accuracy forecasting. It should be noted that in order to explore the possibility of forecasting the aero-engine vibration, the input and output steps are set at 100 and 10 respectively.

In this setting, the input data’s length may be sufficient to enable the model to gather the necessary vital information. Furthermore, experiments about different aero-engine types and those two aero-engine states will also be discussed. The method’s applicability and dependability will be much improved as a result. It can also reveal the powerful potential of the learning algorithm by demonstrating that steady state and transition state features can be learned simultaneously.

It should be noted that the datasets used in this paper are neither standardized nor normalized, the result of vibration levels (unit: MILS.DA) can be directly reflected in the output. And the Mean Square Error (MSE) will be used to measure the performance of our all relative experiments. As a result, MSE is the square of vibration levels (MILS.DA). Finally, the X-axis step in the following figure represents the change over time.

$$\frac{1}{m} \sum_{i=1}^{m} (y_i - \hat{y}_i)^2$$

**TABLE 3. Parameters of cosine annealing LR.**

| Parameter | Meaning |
|-----------|---------|
| $\eta_{\text{max}}$ | Maximum learning rate |
| $\eta_{\text{min}}$ | Minimum learning rate |
| $T_{\text{cur}}$ | Current epoch |
| $T_{\text{i}}$ | Number of periods |

**FIGURE 7. Cosine annealing LR ($T_{\text{max}} = 50$).**

**TABLE 4. Forecasting results (MSE) of different types of aero-engine vibration.**

| Type | System                  | Loss (MSE) |
|------|-------------------------|------------|
| A    | Low Pressure Compressor | 0.003185   |
| A    | Low Pressure Turbine    | 0.002641   |
| B    | Low Pressure Compressor | 0.017422   |
| B    | High Pressure Compressor| 0.001013   |

**TABLE 5. Comparison results (MSE) of different models.**

| Type | System                  | Loss (MSE) |
|------|-------------------------|------------|
| A    | LPC Enhanced ConvNeXt18 | 0.003185   |
| A    | LPC ConvNeXt18          | 0.003218   |
| A    | LPC SENet18             | 0.003338   |
| A    | LPC ResNet18            | 0.003303   |
| A    | LPT Enhanced ConvNeXt18| 0.002641   |
| A    | LPT ConvNeXt18          | 0.002808   |
| A    | LPT SENet18             | 0.002915   |
| A    | LPT ResNet18            | 0.003098   |

Meanwhile, all MSEs are yielded by the mean error of 100 different offset experiments which use the minimum test error model. And the different offsets will make the data input to be different. But all input data comes from the same test datasets and has only the offset. Therefore, the offset will make the extracted data different every time but retain the same test data source. It should be noted that the unit of the aero-engine vibration level forecasted in this paper is the MILS.DA, so the Y-axis of the trend chart is this unit. And the gray area between different curves is the difference between the true and the forecasted.
A. VIBRATION LEVELS OF LOW PRESSURE COMPRESSORS AND LOW PRESSURE TURBINES FROM TYPE A AERO-ENGINES

In this paper, verifying the feasibility of the forecasting method is the first thing needed to do. In this part, not only is the feasibility of the forecasting method tested but it is also compared with the errors of other classic models mentioned above. Under the same conditions which are all models trained completely but not overfitting, the average value of 100 tests with the offset will be used as a measure of the performance of each model. This might make results as accurate as possible. Table 4 presents the results of different types of aero-engine vibration forecasting experiments using the enhanced ConvNeXt model. And Table 5 shows the comparison result on the vibration level of the Type A aero-engine.

As can be seen, the error of the enhanced ConvNeXt model using the sliding window mechanism is indeed less than that of other models. Figure 8 and Figure 9 present the result of forecasting vibration levels on the Type A aero-engine.
It should be noted that the triangle in all box plots represents the position of the average value. Circles represent outliers. Figures show that this method can forecast vibrations with a relatively high level of accuracy. And errors are also in normal distribution. Essential features of the forecast have been fully learned by the enhanced ConvNeXt model with the sliding window mechanism. As a result, the accuracy of these forecasts may reach an extremely high level. Based on the results, the forecast of the future trend of the change of vibration is greatly accurate, and tracking the sudden change is timely enough.

It is clear that this achievement cannot be made without additional future information. This might prompt people to make some limited predictions on the early warning of the aero-engine vibration to avoid insecure situations. The deviation between forecasting values and true sensor signal values could be measured in real-time. The early warning system can alert the crew if the deviation within one step or aggregated over numerous steps is undesirable. The crew may be able to quickly handle the hazardous situation in this way.
B. VIBRATION LEVELS OF LOW PRESSURE COMPRESSORS AND HIGH PRESSURE COMPRESSORS FROM TYPE B AERO-ENGINES

The application of the highly accurate method to other types of aero-engines needs to be confirmed, even though it may yield great results in the type of aero-engine indicated above. In order to achieve this, similar experimental conditions were attempted by doing the same experiments on a Type B aero-engine. The numerical result of forecasting accuracy is seen in Table 4. Figure 10 and Figure 11 show forecasting results on the Type A aero-engine.

Compared with forecasting results above, outcomes from the Type B aero-engine obviously have relatively larger errors. Especially results of low pressure compressors, its error exceeds other results by an order of magnitude. This might be because of how advanced this engine is. Due to the complexity of its internal system, more parameters are required for research. However, this research aims to maintain consistency between the settings needed for the two types of aero-engines in order to conduct comparison studies.
TABLE 6. Results (MSE) of LPC in type A aero-engine.

| Noise          | Loss (MSE) |
|----------------|------------|
| None           | 0.003185   |
| Torch.randn    | 0.003199   |
| Torch.randnint(-10, 10) | 0.004125 |
| Torch.randnint(-20, 20) | 0.006641 |
| Torch.randnint(-30, 30) | 0.009899 |

TABLE 7. Results (MSE) of LPT in type A aero-engine.

| Noise          | Loss (MSE) |
|----------------|------------|
| None           | 0.002641   |
| Torch.randn    | 0.002945   |
| Torch.randnint(-10, 10) | 0.014263 |
| Torch.randnint(-20, 20) | 0.037024 |

Therefore, this work will not explain how to choose better parameters to increase aero-engine vibration forecast accuracy. It’s also another comprehensive and deep topic. After all, this paper only selects ten parameters to explore our goal, and the aero-engine is a huge and complex system. Although end-to-end learning of deep learning can eliminate part of the feature engineering effort to a certain extent. However, to thoroughly study this problem, professional aeronautical knowledge and multi-field research background are necessary.

Most significantly, various aero-engine types have various systems. The main cause of the parameter selection issue is this. But this provides future research an inspiration, which could be applied in the design of control systems to optimize the control process.

Although there may be various reasons above, our method still shows a strong capacity for forecasting aspects and greatly improves forecasting accuracy. As a result, the future information introduction of other parameters is extremely useful.

C. AERO-ENGINE STATES ANALYSIS
In this Part, to make our thoughts more reasonable and convincing, two groups of state experiments on Low Pressure Compressor and Low Pressure Turbine are shown later based on the Type A aero-engine. It can be seen that regardless of whether the transition state prediction and the steady state prediction, the vibration level can be forecasted accurately on the Type A aero-engine. And the forecasting errors of the steady state are lower than the transition state.

Experiments demonstrate that the model can learn the features of these two states effectively and produce high-precision predictions based on the input data. We can therefore temporarily disregard the impact of aero-engine states on forecast accuracy. Furthermore, the model created using our technique can be categorized as a general state model. In actual industries, it is incredibly helpful.

D. NOISE RESISTANCE TEST
In this part, to test the robustness of our model, test datasets will be added with some noise. Additionally, the range of random disturbance will be gradually expanded to examine how the model responds to noise. Values of system parameters could have abruptly change as the random disturbance range is expanded. Therefore, the model’s forecasting task is severely hampered by this abrupt change. And this challenging task will examine our model’s robustness. Our noise selection includes standard normal distribution noise and integer range noise which are involved in Pytorch library functions (torch.randn, torch.randint). The range of noise
random sampling is indicated by the number in parentheses. Figures 16 to 22 and Tables 6 to 7 show the forecasting results of Low Pressure Compressor and Low Pressure Turbine in the test dataset of Type A aero-engines.

As can be observed, the prediction error gradually rises to a different order of magnitude as noise levels rise. In the end, the prediction results will become unstable, but the model can still track the overall future trends and sudden changes.
in signals. Because of this, our model passed the test despite some noise interference.

V. CONCLUSION

Aiming at forecasting the aero-engine vibration level more accurately, this article proposed a powerful method by using an enhanced ConvNeXt model that utilizes the Sliding Window Algorithm mechanism. The results demonstrated that it has been successfully used to forecast different aero-engine vibration levels in various types of aero-engine on a high accuracy level by using actual flight data gathered by aircraft data acquisition systems. And it is extremely uncommon to research several aero-engine types and leverage actual flight datasets, which means that promotes a huge leap to aero-engine research in real industries. Additionally, the aero-engine has specific criteria for its own condition in the real world. The aero-engine reacts to various circumstances in various states. Both transient and steady states are included in the aero-engine state. This paper, like previous relevant experiments, did not separate the aero-engine state in the feasibility and applicability tests but instead established a general model by randomly extracting a block of data. But carrying out experiments additionally for various aero-engine states to demonstrate the validity of this idea. The trials on the model’s noise resistance, in the end, also demonstrate the method’s robustness.

This study has shown that ① It is possible to forecast and model the aero-engine vibration level at a highly accurate level. Compared with the previous research on fault diagnosis and prognosis, the enhanced ConvNeXt model using the sliding window mechanism could forecast future vibration changes and might track the sudden change and fluctuations of vibration signals. Meanwhile, future information on parameters can be added to the process of forecasting, which results in the improvement of forecasting accuracy. This might prompt people to make some limited predictions on the early warning of the aero-engine vibration to avoid insecure situations. The deviation between forecasting values and true sensor signal values could be measured in real-time. The early warning system can alert the crew if the deviation within one step or aggregated over numerous steps is undesirable. The crew may be able to quickly handle the hazardous situation in this way. ② The applicability of the forecast is also verified above. It is possible to forecast not only the future trend of the various vibration levels but also that of different types of aero-engines. Even the vibration of various aero-engine systems could be forecasted. This achievement is of great importance for the understanding and the design of the aero-engine and other vibration systems in other domains. ③ In addition, whether the model can identify different aero-engine running states and make accurate predictions are also verified in this article. Therefore, there are enough reasons to believe that a sufficiently complex algorithm model can learn different states’ features at the same time when the amount of data is ample. ④ By studying multi-parameter fusion, it is known that the complexity of the vibration system in the aero-engine. Therefore, this result could also be used to check which parameters can affect the running of the aero-engine vibration system. Meanwhile, this result shows that the influence of multiple parameters should be considered as much as possible when studying complex vibration systems in aero-engines. In the past, most research has focused on a single vibration parameter, simplifying the vibration system of the engine. However, vibration is affected by many factors.

In addition to the above, this paper still has a few issues that need to be resolved. One of the limitations of this study is the data scale used in the paper, which is a million that has initially reached the scale of deep learning. If more datasets can be gathered, the outcome of the forecast could be more accurate. Second, the mechanical error cannot be completely avoided, and this could have an impact on our research. Moreover, choosing the right parameters is a major challenge that requires in-depth research. In this work, we made an effort to choose the appropriate parameters based on previous research, the aero-engine design concept, and expert manuals. There are still some shortcomings and irrationalities even if it is not the main topic of this essay (the main goal is to offer a highly accurate method for the forecast).

Notwithstanding these limitations, the study suggests that this would be a fruitful area for further work. In follow-up research, how to apply this method to other essential systems will be mainly concerned. And the hidden relationship between time span and vibration systems will be given a lot of thought.

REFERENCES

[1] Y. Shi, J. Zhao, and Y. Liu, “Switching control for aero-engines based on switched equilibrium manifold expansion model,” IEEE Trans. Ind. Electron., vol. 64, no. 4, pp. 3156–3165, Apr. 2017.
[2] C. Sun, Z. He, H. Cao, Z. Zhang, X. Chen, and M. J. Zuo, “A non-probabilistic metric derived from condition information for operational reliability assessment of aero-engines,” IEEE Trans. Rel., vol. 64, no. 1, pp. 167–181, Mar. 2014.
[3] (Sep. 8, 2018). Civil Aviation Resources Website. Statistics Report on China Civil Aviation Safety Information From January to June. [Online]. Available: http://news.carnoc.com/list/461/461183.html
[4] H. Wang, “A survey of maintenance policies of deteriorating systems,” Eur. J. Oper. Res., vol. 139, no. 3, pp. 469–489, Jun. 2002.
[5] D. I. Cho and M. Parlar, “A survey of maintenance models for multi-unit systems,” Eur. J. Oper. Res., vol. 51, no. 1, pp. 1–23, Mar. 1991.
[6] J. Lee and H. Wang, “New technologies for maintenance,” in Complex System Maintenance Handbook. London, U.K.: Springer, 2008, pp. 49–78.
[7] M. Xiong, H. Wang, Q. Fu, and Y. Xu, “Digital twin-driven aero-engine intelligent predictive maintenance,” Int. J. Adv. Manuf. Technol., vol. 114, nos. 11-12, pp. 3751–3761, Jun. 2021.
[8] P. Yu, D. Zhang, Y. Ma, and J. Hong, “Dynamic modeling and vibration characteristics analysis of the aero-engine dual-rotor system with fan blade out,” Mech. Syst. Signal Process., vol. 106, pp. 158–175, Jun. 2018.
[9] N. Wang, D. Jiang, and K. Behdinan, “Vibration response analysis of rubbing faults on a dual-rotor bearing system,” Arch. Appl. Mech., vol. 87, no. 11, pp. 1891–1907, Nov. 2017.
[10] N. Wang and D. Jiang, “Vibration response characteristics of a dual-rotor with unbalance-misalignment coupling faults: Theoretical analysis and experimental study,” Mech. Mach. Theory., vol. 125, pp. 207–219, Jul. 2018.
[11] H. Shao, H. Jiang, X. Li, and T. Liang, “Rolling bearing fault detection using continuous deep belief network with locally linear embedding,” Comput. Ind., vol. 96, pp. 27–39, Apr. 2018.
[12] X. Li, W. Zhang, and Q. Ding, “Cross-domain fault diagnosis of rolling element bearings using deep generative neural networks,” *IEEE Trans. Ind. Electron.*, vol. 66, no. 7, pp. 5525–5534, Jul. 2019.

[13] J. Zhang, S. Yi, G. Liang, G. Hongli, H. Xin, and S. Hongliang, “A new bearing fault diagnosis method based on modified convolutional neural networks,” *Chin. J. Aeronaut.*, vol. 33, no. 2, pp. 439–447, Dec. 2020.

[14] R. Wang, M. Liu, and Y. Ma, “Fault estimation for aero-engine LPV systems based on LFT,” *Asian J. Control*, vol. 23, no. 1, pp. 351–361, Jan. 2021.

[15] X. Xie, “Research on performance assessment and degradation prediction of aeroengine,” Ph.D. dissertation, Harbin Inst. Technol., Harbin, China, 2016.

[16] J. Xu and L. Xu, “Health management based on fusion prognostics for avionics systems,” *J. Syst. Eng. Electron.*, vol. 22, no. 3, pp. 428–436, Jun. 2011.

[17] *Training Manual CFM56-7B Engine Systems*, CFMI Customer Training Center, Cincinnati, OH, USA, 2012.

[18] *CFM56-7B Advanced Engine System*, GE Customer Training Center, Cincinnati, OH, USA, 2016, pp. 99–130.

[19] W. Stevens, “TCP slow start, congestion avoidance, fast retransmit, and fast recovery algorithms,” *Int. Netw. Work. Group*, Washington, DC, USA, Tech. Rep. 24, 1997.

[20] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2016, pp. 770–778.

[21] Z. Liu, H. Mao, C.-Y. Wu, C. Feichtenhofer, T. Darrell, and S. Xie, “A ConvNet for the 2020s,” 2022, arXiv:2201.03545.

[22] Z. Liu, Y. Lin, Y. Cao, H. Hu, Y. Wei, Z. Zhang, S. Lin, and B. Guo, “Swin transformer: Hierarchical vision transformer using shifted windows,” in *Proc. IEEE/CVF Int. Conf. Comput. Vis. (ICCV)*, Oct. 2021, pp. 10012–10022.

[23] A. Dosovitskiy, L. Beyer, A. Kolesnikov, D. Weissenborn, X. Zhai, T. Unterthiner, M. Dehghani, M. Minderer, G. Heigold, S. Gelly, J. Uszkoreit, and N. Houlsby, “An image is worth 16 × 16 words: Transformers for image recognition at scale,” 2020, arXiv:2010.11929.

[24] J. Hu, L. Shen, and G. Sun, “Squeeze-and-excitation networks,” in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, Jun. 2018, pp. 7132–7141.

[25] I. Loshchilov and F. Hutter, “Decoupled weight decay regularization,” 2017, arXiv:1711.05101.

**Dian Kuang** received the master’s degree in civil aircraft maintenance and technology from the Civil Aviation Flight University of China, in 2018. His main research interests include fault diagnosis and health management, big data analysis, and maintenance support of aeroengine.

**Yuyou Zhan** is currently pursuing the M.E. degree in aeronautical science and technology with the College of Aeronautical Engineering, Civil Aviation Flight University of China, Sichuan, China. His research interests include aeroengine fault analysis, artificial intelligence, and data mining.

**Yan Tan** received the master’s degree in aviation engineering from Northwestern Polytechnical University, Xi’an, China, in 2005. She is currently a Full Professor with the Aero Engine Maintenance Training Center, Civil Aviation Flight University of China. Her main research interests include fault diagnosis and health management, big data analysis, and maintenance support of aeroengine.

**Yi Gou** is currently pursuing the B.E. degree in air traffic and transportation with the College of Air Traffic Control, Civil Aviation Flight University of China, Sichuan, China. Her research interest includes air traffic control.

**Wenqing Wu** is currently pursuing the B.E. degree in aircraft manufacturing engineering with the College of Aeronautical Engineering, Civil Aviation Flight University of China, Sichuan, China. Her research interests include aircraft fault diagnosis, artificial intelligence, and data mining.

***