DYNAMIC STALL PREDICTION THROUGH COMBINING PHYSICAL MODELS AND MACHINE LEARNING

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Abstract

The dynamic stall problem has received much attention in the field of flight safety. However, highly accurate dynamic stall prediction remains a challenge due to the complexity of the flow. To make full use of the characteristics of different data sources to establish a reasonable dynamic stall aerodynamic time-domain prediction model, an embedded integrated neural network architecture is proposed, which can realize the fusion of typical multi-source data such as numerical simulation results, physical models and wind tunnel test data. The model effectively reduces the sample demand for unsteady wind tunnel test data in the dynamic stall problem, and significantly improves the accuracy and generalization capability in the dynamic stall prediction of wing and wide-body airliner standard models. For the large-scale nonlinear and unsteady dynamic stall aerodynamic performance prediction problem, the data fusion method embedded in a physical model shows stronger robustness and is more suitable for learning from small sample data than the traditional black-box model.

Keywords: Dynamic stall; Machine learning; Data fusion; Reduced Order Model

1. Introduction

For high-performance lifting body vehicles, dynamic stall can greatly limit the aerodynamic performance boundary and lead to maneuver stability problems; for rotor blades of helicopter-type vehicles, dynamic stall usually directly limits the maximum forward flight speed; and for wind turbine/pressure engine blades/propellers, dynamic stall doubles the efficiency of the operating conditions and affects the flight envelope. The in-depth analysis of subsonic dynamic stall characteristics is of great significance in solving the aerodynamic problems such as high drag and large low head moment caused by the dynamic stall of helicopter and wind turbine propellers, and it is also of great importance in supporting the simulation of large headway angle flights, the study of stall flutter of wings with large spreading ratios, as well as the aerodynamic design of bionic aircrafts. Unsteady aerodynamic prediction is crucial for the safety, optimization and control design of modern aircraft. Recently, the significant expansion of the angles of attack range in modern flight has led to the need for more adequate modeling of unsteady aerodynamic characteristics. This is particularly critical during aircraft takeoff and landing phases, where rapid increases in attack angles can lead the aircraft into stall or post-stall conditions [1]. Therefore, in recent years, studies on the aerodynamic characteristics of static and dynamic stalls are gaining importance.

Although Computational Fluid Dynamics (CFD) is widely employed for solving unsteady flows, its substantial computational cost limits broader applications in flight dynamics and control. For more efficient acquisition of unsteady aerodynamics, the development of aerodynamic Reduced-Order Models (ROMs), based on experimental data or CFD, has been rigorously explored [2].

Currently, unsteady aerodynamic ROMs can be categorized into two main types: system identification and feature extraction. Dynamic linear models within these categories can accurately predict mildly nonlinear responses, making them suitable for a diverse range of flight conditions. However, at high angles of attack, unsteady aerodynamics exhibit strong nonlinear behavior due to intense flow separation, viscous effects, and vortex shedding. In such scenarios, nonlinear ROMs emerge as promising tools to model the complex dynamics of unsteady aerodynamics, particularly for dynamic stall [3]. Here, (deep) neural networks have demonstrated significant potential in capturing and representing these complex nonlinear dynamics.

In order to balance the contradiction between calculation efficiency and calculation accuracy, unsteady aerodynamic models were proposed to improve the ability of the aerodynamic load prediction methods in aeroelastic simulations [4]. Unsteady aerodynamic models are mainly divided into two categories. One is a white box model (semi-empirical model) based on aerodynamic control equations and experimental data, such as Onera [5] and Beddoes–Leishman [6], which are widely used for dynamic stall problems. By combining a small amount of aerodynamic test data with classic aerodynamic prediction experience, some low-precision dynamic stall prediction methods have been developed. Due to their simplicity, these lower-precision models are often used in the initial design stage of the industrial design field. Under the guidance of this research idea, many studies have been carried out: The United Technologies Research Center (UTRC) [7] developed a time-domain unsteady aerodynamic model based on a simple harmonic motion airfoil test, and introduced additional parameters characterizing the unsteady change of the angle of attack in order to achieve preliminary aerodynamic data prediction. Based on the MST theory proposed by De Laurier [8], Kim [9] developed the MST method. Considering the dynamic stall problem of pitching and heaving motion at the same time, it can predict the unsteady aerodynamic loads of a wing with a finite span. Suresh Babu [2] proposed a reduced-order discrete vortex method. By reducing the number of discrete vortices and merging vortex positions, the computational efficiency was greatly improved and the model accuracy was retained. Rohit [10] predicted the dynamic stall aerodynamics of the OA209 wing with limited wingspan by combining the DDES method and the unsteady RANS model and compared the effect of the depth of stall on the aerodynamic boundary. With the development of data-driven models, the research on another type of black box models based on experimental or numerical simulation data have also developed rapidly: Zhang et al. [11] developed a Recursive Radial Basis Function (RRBF) method. By introducing output feedback on the basis of standard RBF neural network to reflect unsteady dynamic effects, a recursive neural network reduced-order model is obtained. Through this model, the unsteady aerodynamic prediction ability is realized and used for aeroelastic analysis problems. Kurtulus [12] used ANN to simulate the unsteady aerodynamic coefficients caused by the airfoil sinking movement. Winter [13] uses fuzzy neural systems to predict unsteady aerodynamic loads and flutter boundaries. These black box models are based on a large amount of aerodynamic data and can make up for the accuracy of empirical models. However, aerodynamic data for dynamic stall problems is difficult to obtain. These data-driven models have not yet been used for dynamic stall problems.

While previous works have produced successful practices in nonlinear aerodynamic system identification, there are still some drawbacks that limited its application to experimental data. In general, black box models of neural networks often require complex and a large amount of data, which is difficult to obtain from experiments. In recent years, Multi-Fidelity (MF) models have been proposed to reduce the amount of data required to get a reasonable model through using models with different fidelity. Since high-fidelity models are accurate but expensive, while low-fidelity models are inexpensive but less accurate, multi-fidelity methods combine these two types of models to achieve accurate representation of high-fidelity results at a reasonable cost. These works motivate our research on developing multi-fidelity unsteady aerodynamic models based on experimental data.

2. Constructing unsteady aerodynamic prediction networks with integrated learning

This part of the work proposes an integrated learning data fusion approach embedded in an unsteady simulation model. The Data Fusion Neural Network (DFNN) framework is shown in Fig. 1. Using multi-source differences, the mapping relationship between aerodynamic data is established to ensure that the model inference process can simultaneously consider the mapping ability of multi-source data for the output. The low fidelity models in this paper comprise two categories, those generated by numerical methods approaches and those generated by classical dynamic derivative models.

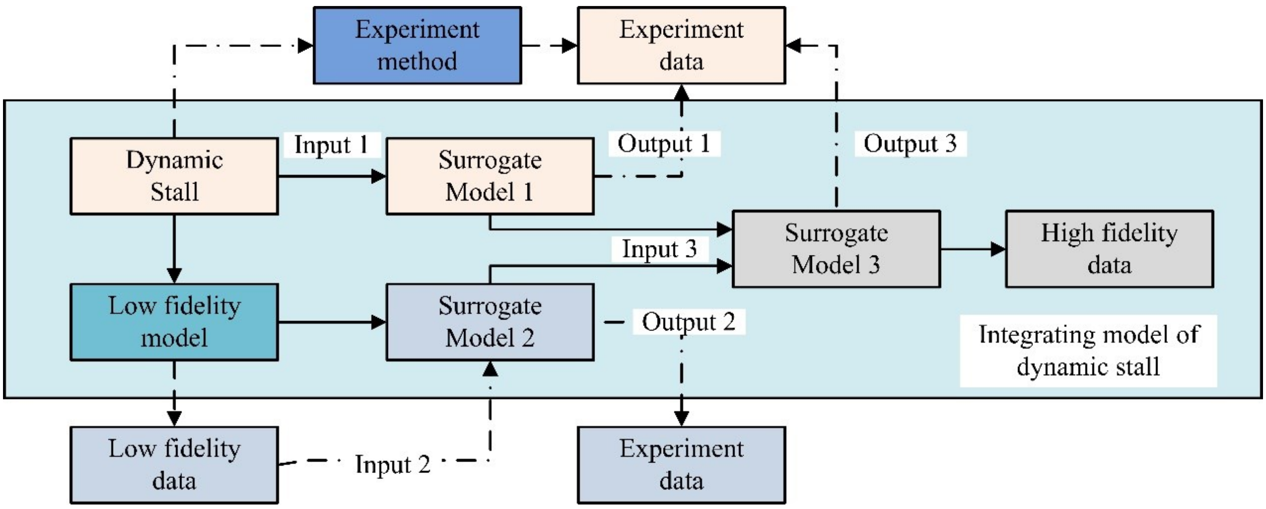
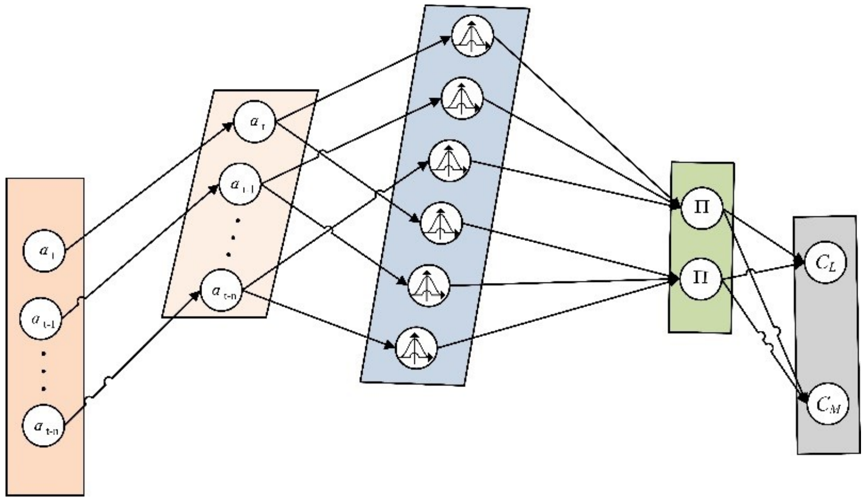


Fig. 1 Data Fusion Neural Network (DFNN) framework

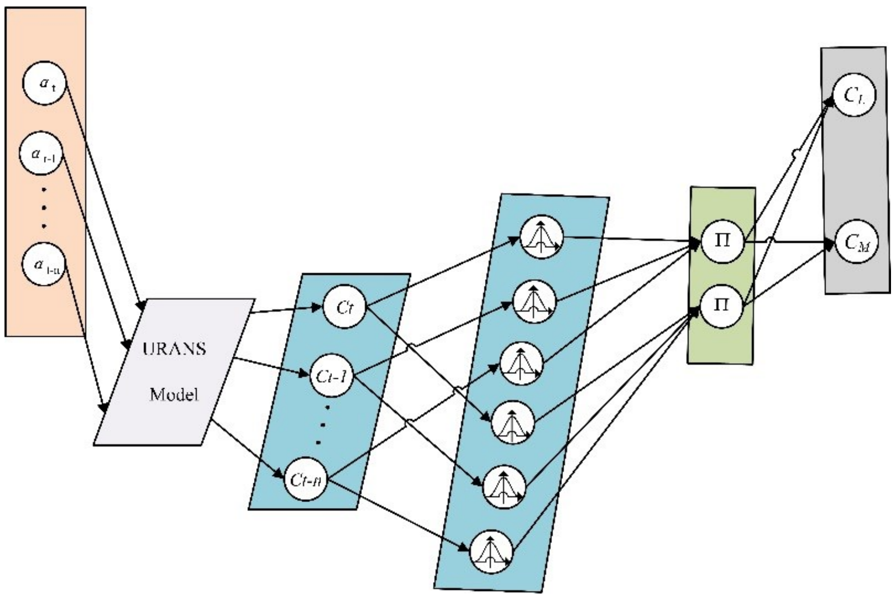
2.1 Neural network models embedded in numerical simulation methods

The unsteady prediction method, commonly used in engineering, is selected for the low-precision model to obtain the aerodynamic prediction of dynamic stall. A data fusion unsteady aerodynamic model based on a small amount of test data is established by nesting the aerodynamic data outputs and motion states of numerical simulation to achieve effective approximation of dynamic stall test data. Since the proposed data fusion architecture is an embedded approach, the prediction data need to be involved in the whole computation for both training and prediction cases. The nested hierarchical framework shows strong generalization capability under different equilibrium headway angles, reduction frequencies and pitch amplitudes, and the convergence and accuracy of the model is verified by modelling with different ratios of training data, which proves that the proposed data fusion framework can effectively predict the dynamic stall loads with high accuracy in the time domain, and the prediction accuracy is higher than that of the traditional model and the CFD method.

The purpose of data fusion (as shown in Fig.2) is to use the numerical solution results of low-precision models to achieve accurate mapping of aerodynamic data in the experimental state, to make up for the problem of low confidence in the data caused by model errors or numerical errors in the numerical method itself. At this point, the numerical simulation method as an embedded model needs to participate in the mapping process. Therefore, for each step of the modelling, the time lag effect of the unsteady motion of the airfoil and the corresponding unsteady effect of the aerodynamic output needs to be considered at the same time.



(a) Upper neural network architecture



(b) Lower neural network architecture

Fig. 2 Layered architecture for integrated neural networks

2.2 Neural network models embedded in physical models

The dynamic derivative model based on physical assumptions provides an efficient means of aerodynamic prediction, but the prediction accuracy of the model needs to be further improved. To this end, an integrated neural network architecture embedded in the dynamic derivative model is proposed to reduce the discrepancy between the low fidelity model and the high precision wind tunnel test data. Therefore, the main research focus of dynamic stall lies in accurate and robust aerodynamic reduced-order modeling under limited data. This motivates the current study to obtain multi-fidelity model that balances the overall accuracy and the modeling requirement of data. With this model, the efficiency in generating the training data can be further improved, since a smaller number of experimental data is required to reach a high level of accuracy. To this end, we propose a multi-fidelity neural network through combining fuzzy neural network with physical models to improve the generalization capabilities of dynamic stall modeling. The neural network architecture embedded in the physical model is shown in Fig. 3.

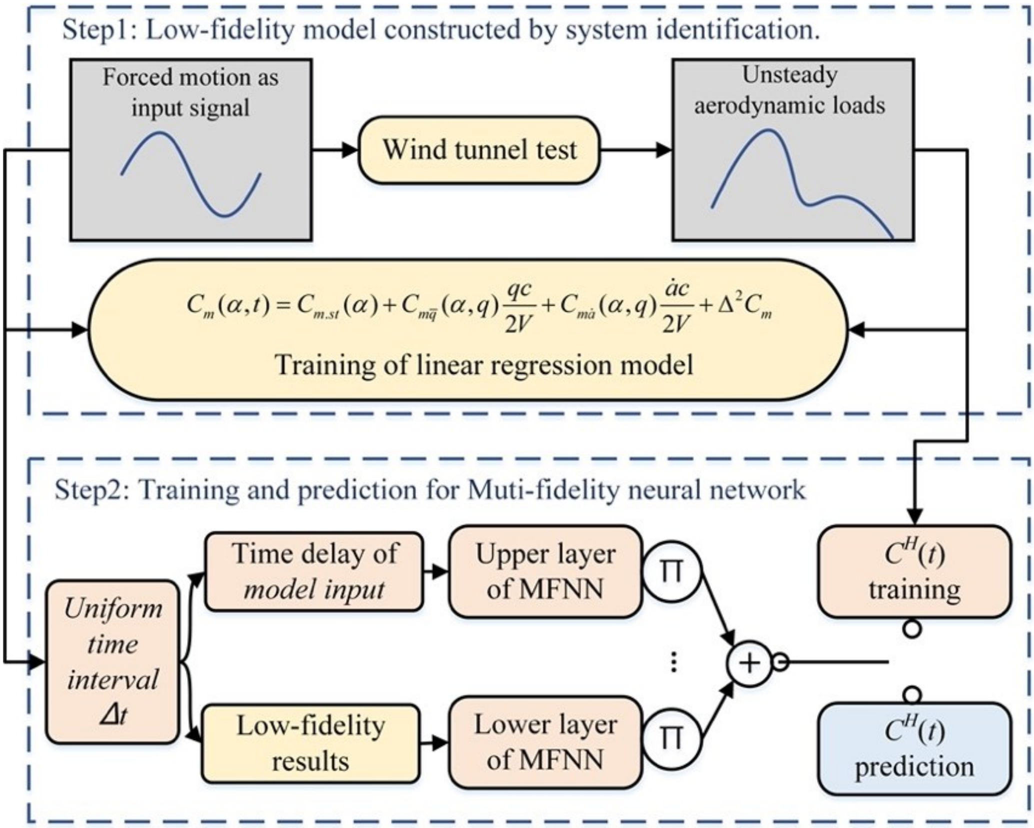


Fig. 3 The neural network architecture embedded in the physical model

3. Multi-source aerodynamic data

3.1 NACA0012 airfoil

To validate the proposed data fusion method, the dynamic stall wind tunnel test [14] data of the NACA0012 airfoil was selected as the research target. The wind tunnel test was done by NASA with a Reynolds number of 2.5×10^6 and Mach number of 0.09. The headway history of dynamic stall is shown in Equation (1). The definition of the deceleration frequency is shown in Equation (2). Where *k* is the reduction frequency, *c* is the airfoil chord length, and U_∞ is the incoming velocity. To show the difference of unsteady motion at different frequencies and amplitudes in the experimental data, the angle of approach history at the same time interval is used here to show that. A comparison of the unsteady cases with the calculated results is shown in Fig. 4 and Fig. 5.

$$\alpha(t) = \alpha_0 + A_m \sin(\omega t) \tag{1}$$

$$k = \omega \cdot c / 2U_\infty \tag{2}$$

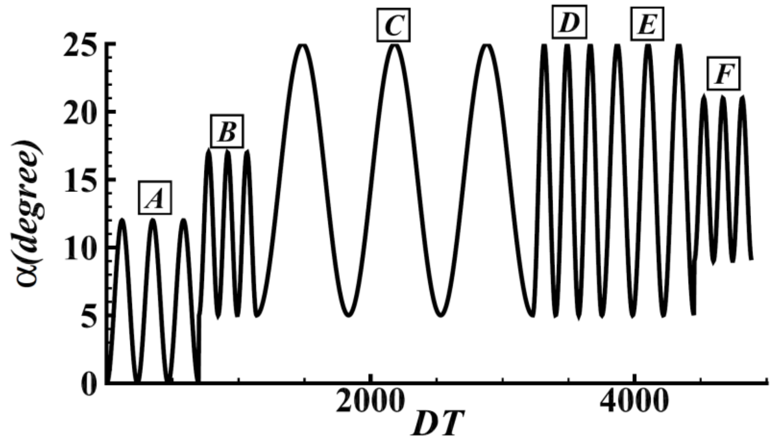


Fig. 4 Comparison of pitching motions of unsteady cases

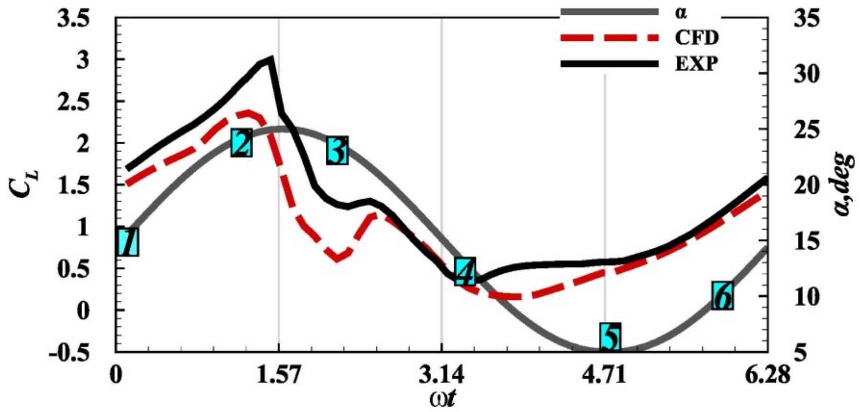


Fig. 5 Comparison between numerical calculation results and wind tunnel tests

When the airfoil is in motion, the motion of the dynamic stall-separated vortices leads to additional aerodynamic loads compared to the aerodynamic forces of the constant solution. It can be noticed from Fig. 6 that the vortex shedding and motion lead to strong nonlinearities in the flow field. It can be seen from the figure that during the flow separation process (shown in Fig. 6), the shedding of vortices is largely synchronized with the onset of stall. However, it is often difficult to distinguish the parts of the dynamic stall process that correspond to the attached and separated flows, which explains the difficulty in predicting the dynamic stall aerodynamics.

For the URANS method, it is difficult to accurately predict the location of the airfoil separation point so as to distinguish between the attachment and separation flow stages during pitching motion. Therefore, it is difficult to accurately match the CFD simulation results with the experimental results. Physical knowledge is integrated into the data fusion model to improve the ability to distinguish separation flow and attachment flow during dynamic stall by building an embedded integrated neural network.

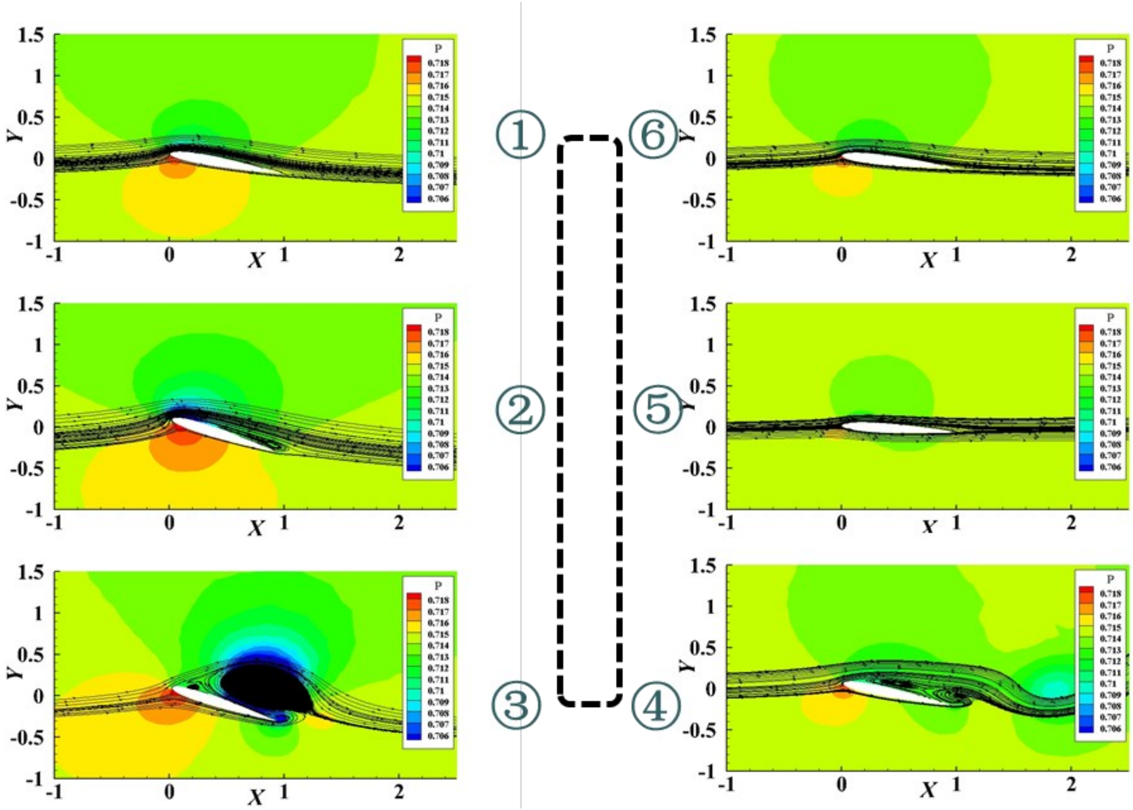


Fig. 6 Dynamic stall flow field simulation results of NACA0012 airfoil

3.2 NASA Common research model

To study the dynamic stall characteristics of transport aircraft at large angles of approach, the National Aeronautics and Space Administration (NASA) has selected the Common Research Model (CRM), a standard layout model of a typical twin-engine, long-range, twin-aisle, wide-body commercial transport aircraft, to be the subject of the study. The CRM is a standard layout model published by NASA for a typical twin-engine, long-range, two-aisle, wide-body commercial transport aircraft. The three-dimensional digital model and data of the aircraft are publicly available for international research and collaboration. The CRM model is publicly available and can be accessed at the following links:

https://commonresearchmodel.larc.nasa.gov/.

The NASA Common Research Model (CRM) is a typical modern airliner with an advanced supercritical wing and wide-body fuselage. The design cruise Mach number of the CRM is 0.85, and the corresponding design lift coefficient is C_L=0.5. A dynamic stall aerodynamic wind tunnel test was carried out using a scaled-down model with a scale of 2.45%. The main scaling parameters of the wind tunnel test model are shown in Table 1.

The wind tunnel tests were conducted in the FL-14 low-speed wind tunnel of the China Aerodynamic Research and Development Centre (shown in Figure 7). Wind tunnel test section for the diameter of 3.2m circular cross-section, turbulence is lower than 0.168%, the wind tunnel of the downstream static pressure gradient of about 0.0025m^{-1}. Φ3.2m wind tunnel (FL-14) is an open, closed mouth dual-use test section of the reflux type low-speed wind tunnel, built in 1992 and put into use, equipped with a tensioned wire support system, movable floor test device, It is equipped with a tension wire support system, a movable floor test device, a multi-degree-of-freedom dynamic test system, etc., and is mainly used for special tests of aerospace vehicles.

Table 1 Main parameters of wind tunnel test scaling model

Main parameters	Value
Wingspan（b/m）	1.44
Wing reference area（S/m^2）	0.2304
Average aerodynamic chord length of the wing（c/m）	0.1717
Moment reference Centre（1）	0.25c
Weights（kg）	8.64

The incoming wind speed V_0 in the wind tunnel test state is 30m/s. Firstly, the static aerodynamic characteristics of CRM at high angles of attack were studied. The angle of attack varies from -10 to 50 degrees. The experimental results of lift coefficient and moment coefficient are shown in Fig. 7. Next, high angle of attack pitch oscillation tests were conducted on the same testing equipment. At different angles of attack, the amplitude of pitch motion is 10, 15, and 20 degrees, and the frequency range is between 0.25Hz and 1.25Hz. The angle of attack history under forced motion of the model is expressed as equation (3). It is the equilibrium angle of attack, where A_m represents the amplitude of pitch motion and f here represents the oscillation frequency of harmonic motion.

$$\alpha(t) = \alpha_0 + A_m \sin(2\pi ft) \tag{3}$$

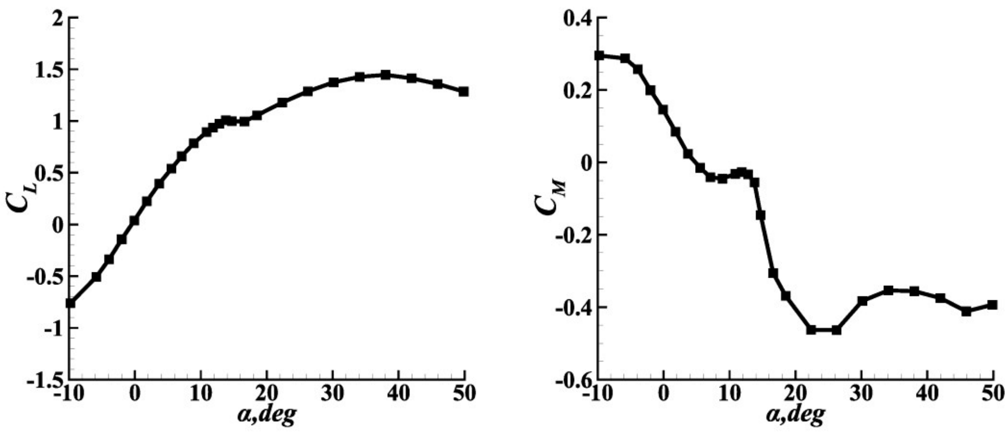


Fig. 7 Wind tunnel test results of CRM longitudinal aerodynamic characteristics

Unsteady aerodynamics exhibit complex nonlinear characteristics at different frequencies. As the pitch motion frequency increases, the aerodynamic unsteady effects become more significant, leading to an increase in the hysteresis loop area. This poses difficulties for aerodynamic modeling, especially with the nonlinearity of the pitch torque coefficient being significantly higher than the lift coefficient. Therefore, it is necessary to propose a data fusion model that considers both unsteady and nonlinear aerodynamic characteristics.

As the pitch motion frequency increases, the aerodynamic forces of CRM aircraft exhibit strong nonlinear and unsteady characteristics, which must be considered in high angle of attack extreme flight states. Especially after the pitch motion frequency exceeds 1Hz, there is a significant difference between the unsteady aerodynamic torque and the aerodynamic torque at low frequencies. It is particularly important to effectively predict the changes in the unsteady aerodynamic characteristics of CRM for flight safety assessment.

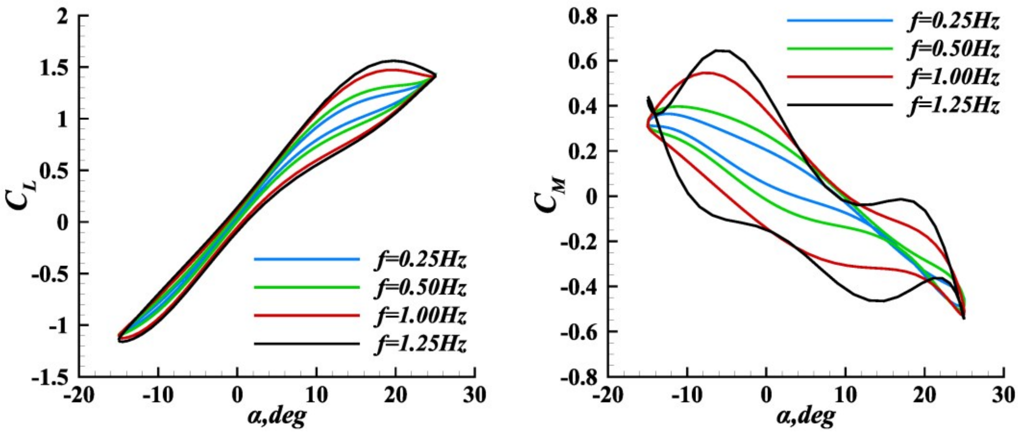


Fig. 8 CRM Unsteady Aerodynamic Wind Tunnel Test Results

4. Neural network prediction results

To compare the differences between typical black box models, typical data fusion correction models, and the proposed embedded integrated learning data fusion model, two neural network models under input conditions without data fusion integration architecture were selected for comparison in high reduction frequency extrapolation prediction cases, as shown in Fig. 9.

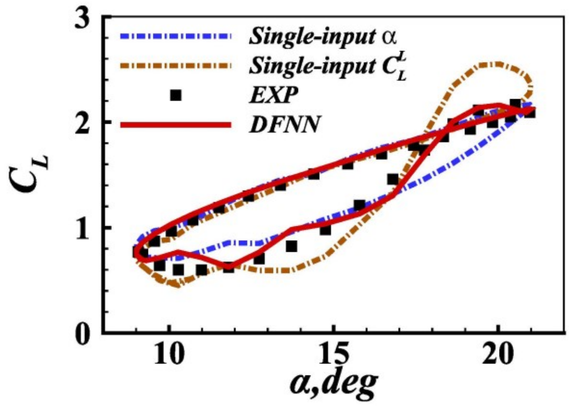


Fig. 9 Comparison between DFNN model and traditional model

DFNN represents the prediction results using an embedded data fusion architecture. It can be seen that due to the small sample size of training data, directly establishing models based on angle of attack or numerical simulation aerodynamics as inputs cannot have accurate global modeling ability for experimental data, and the overall prediction results have a large error. This is because in small samples, the complex parameters involved in dynamic stall problems are difficult to directly characterize through black box models or traditional modified models. These two traditional models can only achieve prediction and generalization within a limited interval, lacking the high-precision representation ability of dynamic stall globally. The embedded data fusion architecture has high prediction accuracy throughout the entire dynamic stall range, and the capture of stall points is also more accurate. The overall aerodynamic output results are consistent with the experimental results.

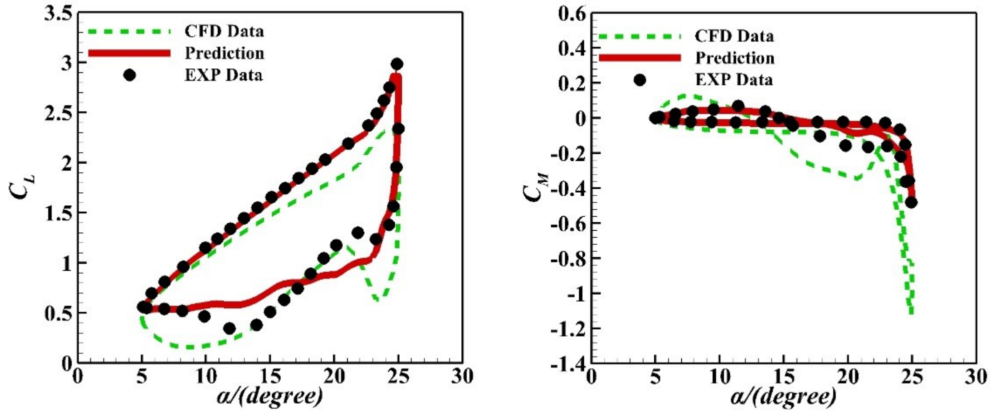


Fig. 10 Test case D： α_0**=15°,** α_m **=10°, k=0.15**

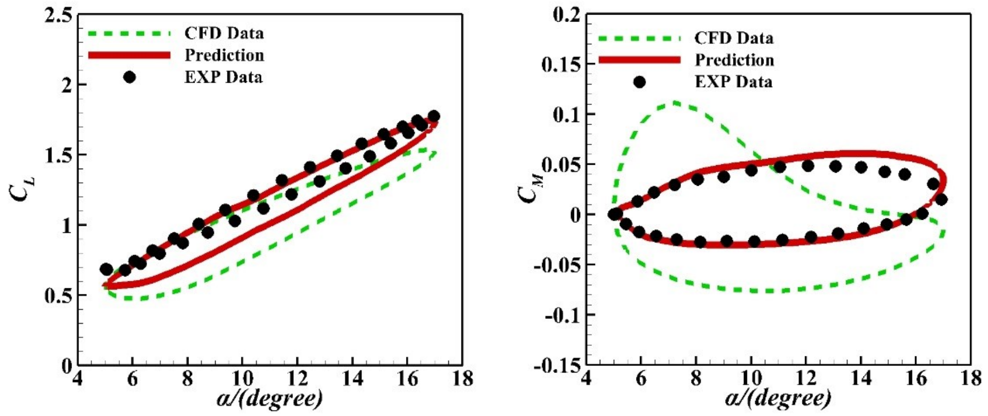


Fig. 11 Test case B： α_0**=11°,** α_m **=6°, k=0.24**

Fig. 10 and Fig. 11 show the comparison of data fusion prediction aerodynamic coefficients with experimental aerodynamic data. During the pitch-up and pitch-up phase of the pitching motion, when the angle of attack is low, the CFD simulation results are better compared with the test because the airfoil separation is small. With the occurrence of dynamic stall effect, the CFD data starts to completely deviate from the test data. At this time, due to the black box mapping effect of the data fusion framework, the deficiency of the numerical simulation results is made up, so that the predicted aerodynamic force can accurately capture the dynamic stall characteristics. In the airfoil down-shooting phase, due to many separations and vortex movements, the CFD method has completely deviated from the test results. At this stage, the aerodynamic numerical error is the largest, and the aerodynamic change trend is not consistent with the test data. At this time, the data fusion prediction results corrected by numerical simulation results also show some accuracy fluctuations, but they are generally in good agreement with the test results, which has improved the confidence of the data. The nested layered data fusion framework effectively captures the aerodynamics of the experimental data under dynamic stalls, and uses a small amount of high-precision data under the premise of not increasing the calculation cost, and obtains aerodynamic dynamic stalls with a certain generalization ability. Forecasting model.

In the following work, we will investigate the pitch motion of NASA-CRM at different angles of attack and frequencies to evaluate the robustness and accuracy of the proposed integrated neural network modeling method embedded in physical models. Therefore, the validation process for the model is organized as follows: Firstly, the lift and torque coefficients in the amplitude and frequency parameter spaces are used to model and verify the accuracy and generalization ability of the model. Next, in order to analyze the improvement of model convergence and robustness, ablation experiments were conducted on the model. This is to compare the situation without using data fusion models to demonstrate the value of embedded physical modeling in integrated neural network modeling. Finally, modeling the complex three-dimensional parameter space of pitch motion verified the strong engineering application ability of the model.

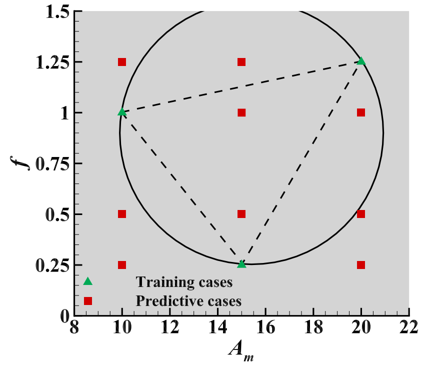
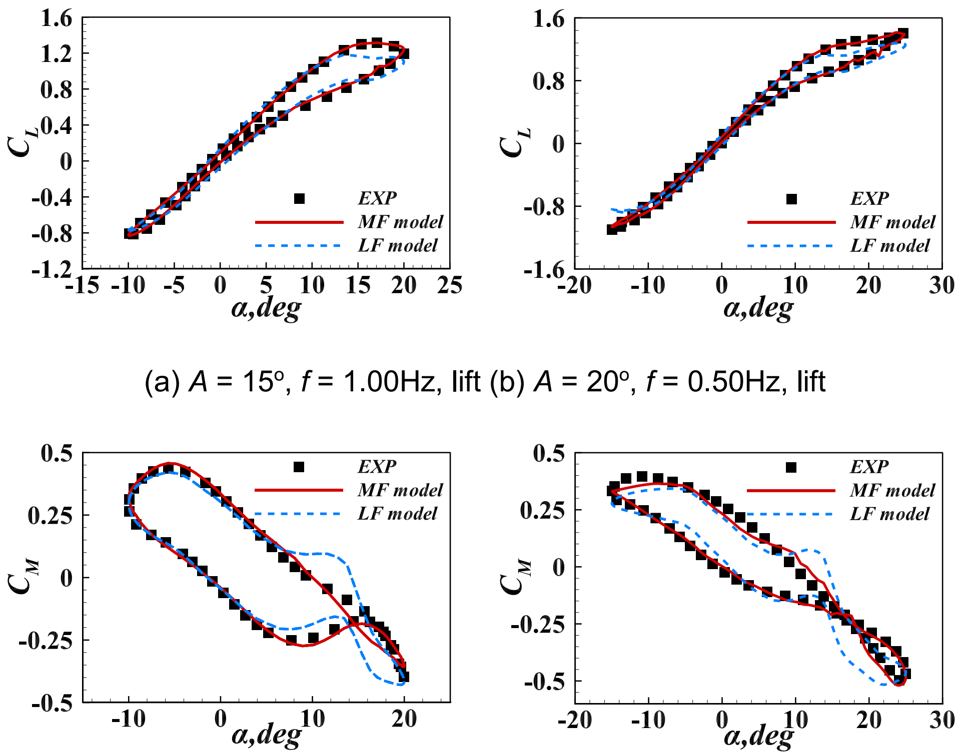


Fig. 12 Sampling parameters for the training and test cases of harmonic pitching motions of the CRM.



(a) *A* = 15°, *f* = 1.00Hz, lift (b) *A* = 20°, *f* = 0.50Hz, lift

(b) *A* = 15°, *f* = 1.00Hz, moment (d) *A* = 20°, *f* = 0.50Hz, moment

Fig. 13 Prediction of lift and moment coefficients based on the proposed model.

The constructed model is trained based on the wind tunnel test results of pitching motions of the CRM. The parameter range and sampled states are shown in Fig. 3. These experimental data are used to verify the prediction accuracy of the unsteady model in a wide range of oscillation amplitude, frequencies and mean angles of attacks. From the preliminary test, the proposed model shows improved accuracy in a large angles of attack and frequency range. This can be clearly observed in Fig.4, where lift and moment coefficients are well predicted by the proposed multifidelity model. The results indicate that the method has good generalization capability for the parameters of interest. At the same time, the comparison with the prediction results only from high-fidelity data shows that the proposed method can effectively reduce the amount of data required for model of training and improve the modeling robustness to different types of motions.

5. Conclusion

The comprehensive performance of the model indicates that the idea of embedding physical models has a significant improvement in modeling ability under small sample data. This framework effectively improves the generalization ability and robustness of high angle of attack aerodynamic modeling, providing a new approach for the design and efficiency improvement of unsteady wind tunnel experiments. When the accuracy of traditional reduced order models or numerical simulation models cannot meet the experimental requirements, combining physical modeling with this framework will be a feasible method to improve the extrapolation ability of existing physical models. Especially in complex flow environments, the predictive ability of the model is expected, and the integrated neural network framework embedded in physical models is an effective integration of physical information from empirical models. It has enormous potential in complex dynamic modeling where the mechanism is still unclear.

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7. Copyright Statement

References

[1] Corke T C, Thomas F O. Dynamic stall in pitching airfoils: aerodynamic damping and compressibility effects[J]. *Annual Review of Fluid Mechanics*, 2015, 47: 479-505.

[2] Kou J, Zhang W. Data-driven modeling for unsteady aerodynamics and aeroelasticity[J]. *Progress in Aerospace Sciences*, 2021, 125: 100725.

[3] Li K, Kou J, Zhang W. Deep neural network for unsteady aerodynamic and aeroelastic modeling across multiple Mach numbers[J]. *Nonlinear Dynamics*, 2019, 96: 2157-2177.

[4] Holierhoek J G, De Vaal J B, Van Zuijlen A H, et al. Comparing different dynamic stall models[J]. *Wind Energy*, 2013, 16(1): 139-158.

[5] Tran C T, Petot D. Semi-empirical model for the dynamic stall of airfoils in view of the application to the calculation of responses of a helicopter blade in forward flight[J]. *Journal of the American Helicopter society,* 1980, 12(1): 18-35.

[6] Leishman J G, Beddoes T S. A Semi‐Empirical model for dynamic stall[J]. *Journal of the American Helicopter society*, 1989, 34(3): 3-17.

[7] Gangwani S T. Prediction of dynamic stall and unsteady airloads for rotor blades[J]. *Journal of the American Helicopter Society*, 1982, 27(4): 57-64.

[8] DeLaurier J D. An aerodynamic model for flapping-wing flight[J]. *The Aeronautical Journal*, 1993, 97(964): 125-130.

[9] Kim D K, Lee J S, Han J H. Improved aerodynamic model for efficient analysis of flapping-wing flight[J]. *AIAA Journal*, 2011, 49(4): 868-872.

[10] SureshBabu A V, Ramesh K, Gopalakrishnan A. Model reduction in discrete-vortex methods for unsteady airfoil flows[J]. *AIAA Journal*, 2019, 57(4): 1409-1422.

[11] Zhang W, Ye Z. Reduced-order-model-based flutter analysis at high angle of attack[J]. *Journal of Aircraft*, 2007, 44(6): 2086-2089.

[12] Kurtulus D F. Ability to forecast unsteady aerodynamic forces of flapping airfoils by artificial neural network[J]. *Neural Computing and Applications*, 2009, 18: 359-368.

[13] Winter M, Breitsamter C. Neurofuzzy-model-based unsteady aerodynamic computations across varying freestream conditions[J]. *AIAA Journal*, 2016, 54(9): 2705-2720.

[14] McAlister K W, Carr L W, McCroskey W J. Dynamic stall experiments on the NACA 0012 airfoil [R]. *America: NASA*, 1978: 25-71.