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DATA FUSION UNSTEADY AERODYNAMIC MODELING BASED ON EXPERIMENTAL DATA

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Abstract

Dynamic stall prediction at high angles of attack is faced with the dual challenges of insufficient accuracy of calculation data and lack of experimental data. In order to make full use of the characteristics of different data sources to establish a dynamic stall aerodynamic time-domain prediction model, this paper proposed a data fusion modelling method, which combines a Computational Fluid Dynamics solver with a neural network model. By fusing experimental data and Computational Fluid Dynamics simulation data, combined with an integrated neural network model, an unsteady aerodynamic data fusion modelling framework for airfoil dynamic stall is established. Based on the NACA0012 airfoil dynamic stall test data, and the Computational Fluid Dynamics numerical simulation results, the proposed data fusion framework performs high precision in the prediction of wind tunnel test data, including lift and moment coefficients at different pitch angles, balanced angles of attack and reduced frequencies. Results show that the proposed data fusion framework not only has higher prediction accuracy, but also has strong abilities in both generalization and convergence.

Keywords: Dynamic stall; Machine learing; Data fusion; Reduced Order Mdoel

1. Introduction

The problems of dynamic stall in unsteady aerodynamic involve mass effect, flow separation, formation and shedding of leading-edge vortices [1-2]. Due to its complexity and importance, the issues of dynamic stall have received widespread attention in the fields of helicopter, turbomachinery, flapping wing aircraft and wind turbine industries. Because of the existence of flow separation, the nonlinear and unsteady effects of aerodynamic loads under dynamic stall are particularly prominent. At the same time, the existence of dynamic response problems and aeroelastic stability analysis problems raise higher requirements for the accuracy of aerodynamic data prediction under dynamic stall [3].

Focusing on the problem of dynamic stall of airfoils, researchers have carried out extensive wind tunnel tests and numerical calculations [4-6]. As early as 1978, NASA conducted a series of

experiments on the dynamic stall of the NACA0012 airfoil, analyzed the separation characteristics of the leading-edge vortex and obtained aerodynamic loads test results at different reduced frequencies [7]. With the development of Computational Fluid Dynamics (CFD), some high-precision numerical methods have also been applied to the dynamic stall problem [3]. John [3] reviewed the aerodynamic prediction problems of airfoil dynamic stall. However, due to the limitations of experimental conditions and computing resources, the dynamic stall research performed by the above two methods still cannot be directly applied to engineering practice. Its limitations are mainly reflected in two aspects: First, due to the limitations of the experimental environment, dynamic stall tests are often limited to simple harmonic motion in the frequency domain, it is difficult to perform load prediction under arbitrary motion conditions, and it cannot meet the requirements of time domain analysis and stability analysis . Second, it is difficult to simulate the flow separation and turbulence by numerical simulation methods, especially the vortex propagation and movement in the flow, which results in poor accuracy of the numerical simulation data.

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 [8]. 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 [9] and Beddoes–Leishman [10], 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 [3]. Under the guidance of this research idea, many studies have been carried out: The United Technologies Research Center (UTRC) [11] 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 [12], Kim [13] 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 [6] 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. [14] 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 [15] used ANN to simulate the unsteady aerodynamic coefficients caused by the airfoil sinking movement. Winter [16] 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.

The above two research methods have played a good guiding role in unsteady aerodynamic modeling. However, there are still drawbacks to the analysis of dynamic stall for a single source of data. For the semi-empirical models, the supplementary parameters introduced by the physical parameter model often depend on the test and motion state parameters to a large extent, and the parameter adjustment and generalization cannot be performed well. At the same time, the black box model relies on complex test data. The modeling requires a large number of complex test conditions for parameter training. These characteristics are difficult to meet in engineering. To make up for these shortcomings, new dynamic stall models are required to take advantage of both aerodynamic data sources. At this time, it is necessary to consider the modeling method based on data fusion technology to improve the accuracy of the theoretical model data while ensuring the generalization ability of the data-driven model.

Data fusion refers to combining data and information from multiple sources in order to better improve, estimate and use the data [17]. This idea is now rapidly applied to rapid simulation and optimization evaluation of steady aerodynamics to improve the consistency of CFD method data and test data, and greatly reduce simulation costs. Ghoreyshi et al. [18] used the experimental data and

CFD simulation results to build a high-dimensional steady-state aerodynamic model of the aircraft, and built a steady-state aerodynamic data test and numerical data variable-precision model. However, the research on the fusion of unsteady data is currently less developed. Kou et al. [19] first adopted a multi-core neural network model to generalize the variable precision model to the unsteady aerodynamic model, and realized the use of low-precision Euler results Approximation of N-S numerical results. Data fusion technology has also been applied to the development of turbulence models based on data-driven technology, using high-precision experiments or numerical simulation data to modify the RANS model to achieve higher-precision CFD modeling [20] [21]. At present, the data fusion methods for aerodynamic data mainly use three methods [22], 1) a correction model based on addition and multiplication; 2) a fusion model based on comprehensive correction; 3) a spatial mapping (input correction) model. This paper adopts the third method.

Based on the research status of the dynamic stall problem, this paper proposes a method for data fusion of integrated models with nested unsteady CFD solvers. Using different data sources of the dynamic stall aerodynamic data, the mapping relationship between aerodynamic data is established to ensure that the model's results take into account the mapping relationship between the two sources for aerodynamic data. The low-fidelity model selects the unsteady Reynolds-Averaged Navier–Stokes (RANS) method commonly used in engineering to obtain preliminary results of the aerodynamic coefficient of dynamic stall. Based on the aerodynamic data output and motion state of the nested Navier–Stokes model, a black box unsteady aerodynamic model based on a small amount of test data is established to effectively approximate the unsteady dynamic stall test data. The nested layered framework model shows high generalization ability under different equilibrium angles of attack, reduction frequency and pitch amplitude. The convergence and accuracy of the model are verified through reinforcement training, which proves that the proposed data fusion framework can be effective. It performs high-precision dynamic stall load prediction in the time domain, and has higher prediction accuracy than traditional models and CFD methods.

2. Methodology

Here we mainly introduce the neural network model used for modeling framework construction-scalar-based fuzzy neural network, and the unsteady RANS model that provides numerical solutions for aerodynamic estimation. The aerodynamic solution provided by the unsteady RANS model is used

to provide a numerical description of the unsteady effects. The overall dynamic process is implemented by a neural network framework to realize the mapping process of the dynamic stall aerodynamic unsteady and nonlinear output.

This paper studies the data fusion framework by combining different types of models. The integrated model framework proposed is shown in Figure 1. The different surrogate models are used to build integrated models that reflect different data sets. Three different surrogate models are used to implement the aerodynamic prediction process. Surrogate model 1 implements the mapping from the dynamic input to the aerodynamic coefficients which is same as the traditional black box models. Surrogate model 2 uses the mapping from low-fidelity CFD solver‘s data to experimental data, and surrogate model 3 integrates the performance of the first two models to realize the high-confidence data output process.

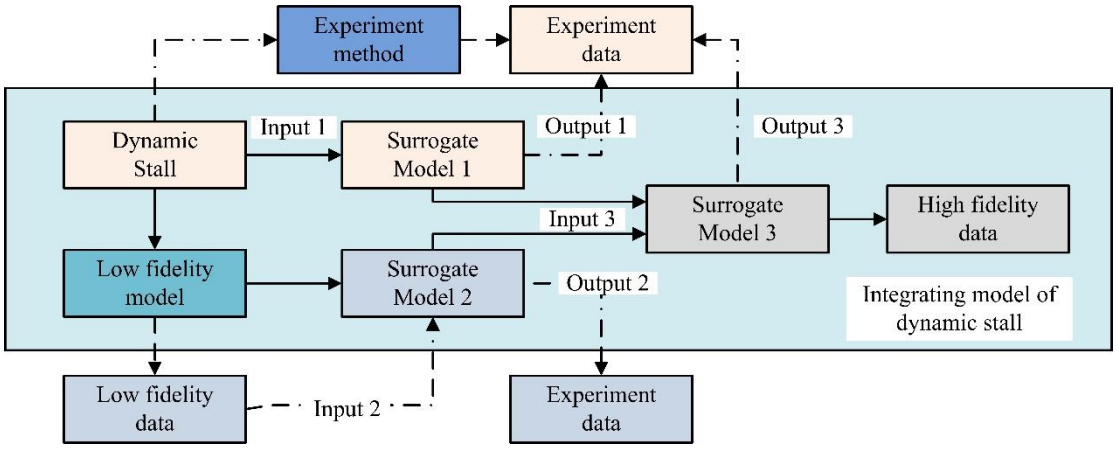


Fig. 1 Data Fusion Framework for dynamic stall

Aerodynamic models based on fuzzy neural network model

In order to reflect the current aerodynamic effects of the aerodynamic aerodynamics and the time lag effect of motion on the aerodynamics, Chen [23] proposed the use of autoregressive models for modeling and analysis to describe the effects of time lag effects on aerodynamics by input and output delay. This dynamic process can be embodied by the following dynamic model with input delay and output feedback, where n represents the delay order of input and output, $\boldsymbol{u}^T(k)$ represents the kinetic input at time k, and $\boldsymbol{y}^T(k)$ represents the kinetic output at time k:

$$\begin{aligned}\boldsymbol{y}(k) &= f[\boldsymbol{x}^T(k)] \\ &= f\left\{[\boldsymbol{u}^T(k), \boldsymbol{u}^T(k-1), \boldsymbol{u}^T(k-2), ..., \boldsymbol{u}^T(k-n), \boldsymbol{y}^T(k-1), \boldsymbol{y}^T(k-2), ..., \boldsymbol{y}^T(k-n)]\right\}\end{aligned} \tag{1}$$

Based on this mapping relationship, Zhang et al. Developed a static RBF neural network into a recursive radial basis neural network [14], and implemented transonic unsteady aerodynamic modeling for aeroelastic analysis problems. On the basis of this model, Wang [24] constructed aerodynamic black box model based on fuzzy scalar radial basis function (FSRBF) neural network by combining the fuzzy neural network method to overcome the limitation of the generalization ability of the model by the physical or numerical difference of the input quantity.

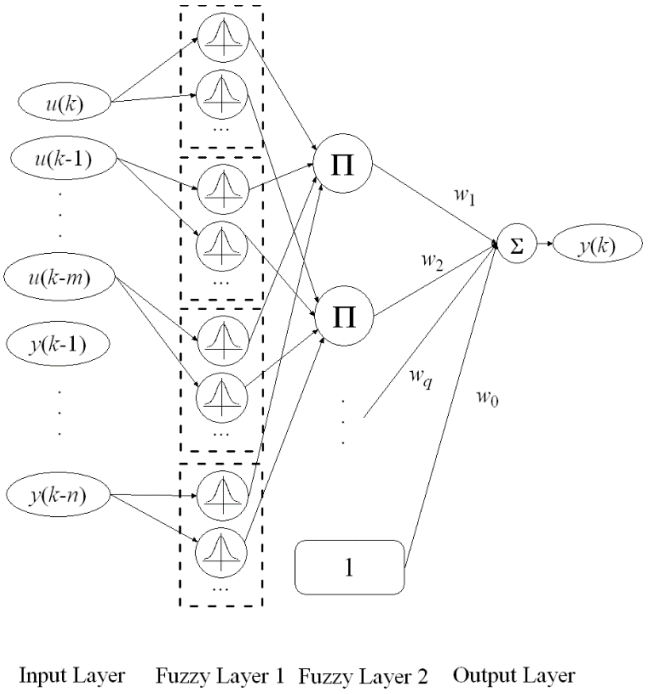


Fig. 2 Scalar-based fuzzy neural network structure [24]

A. Data fusion model based on fuzzy neural networks

The purpose of data fusion is to use the numerical solution results of the low-precision model to achieve accurate mapping of aerodynamic data in the experimental state, so as to make up for the problem of low data confidence caused by the numerical error. Therefore, for each step of the model, it is necessary to consider both the time-lag effect of the unsteady motion of the airfoil and the unsteady effect of the corresponding numerical degassing power output.

It should be pointed out that although the URANS model can obtain numerical solutions describing unsteady aerodynamics to some extent, because the URANS model is difficult to accurately capture the flow separation and the tail vortex motion, the result of the model solution cannot be directly used as the dynamic stall. The analysis basis, especially the more nonlinear moment coefficient, limits the

application of this CFD technique to dynamic stall problems. Therefore, we consider the use of integrated models to build a black box model based on CFD numerical results and unsteady motion input data fusion to improve the prediction accuracy of the experimental model. In this paper, the numerically calculated aerodynamic data are referred to as low-precision aerodynamic data.

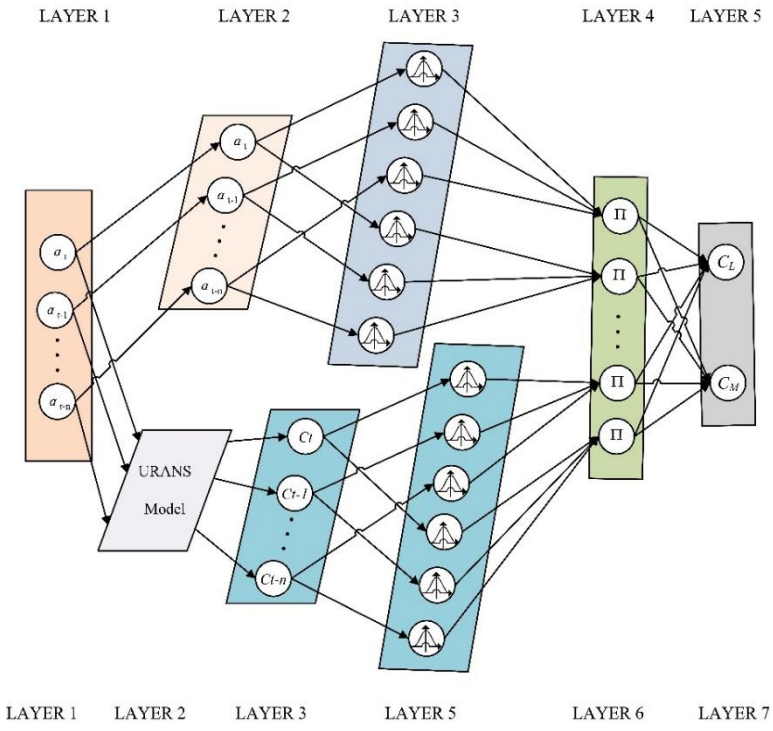


Fig. 3 Data fusion framework based on fuzzy neural networks

Standard fuzzy neural network is mainly composed of four layers of neurons, including: input layer, fuzzy layer, fuzzy inference layer and output layer. A fuzzy neural network based on data fusion ideas is constructed here, as shown in Figure 3. Next, we will introduce the different layers of neurons above and below the neural network. The upper layer surrogate model 1 (superscript layer2-4) constructs the fuzzy mapping of the unsteady angle of attack. The target layer 1-6) contains 6 layers, of which the second layer is the input layer (Eq. 2) in which the numerical solution method is nested, and the dynamic input at each step requires the corresponding low-precision aerodynamic data. Finally, the surrogate model 3 (subscript layers 6-7) responsible for the output implements the weighted output of the two fuzzy neuron layers. The following contents introduce these models separately.

1. Surrogate model 1

There are three layers of neurons in Surrogate model 1 (superscript Layer 2-4), where layer 2 is the input layer, which reflects the angle of attack value of the unsteady effect of wing motion. The n-th order input delay is used to reflect the effects of unsteady time delay. The pitch angle corresponding to each time delay term is used as input, as shown in Eq. 2:

$$f_1 = \left\{ [\boldsymbol{u}^T(k), \boldsymbol{u}^T(k-1), ..., \boldsymbol{u}^T(k-n)] \right\} \tag{2}$$

The second layer is a fuzzy layer, which performs non-linear mapping on the input information to achieve data fuzzing. This layer uses a Gaussian function as the activation function to perform non-linear operations on neurons in each input layer, as shown in equation (3). Among them, the mean and variance of the current neuron c_{ij}, σ_{ij} are respectively expressed. Each center value c_{ij} of the fuzzy layer is derived from the input value of the training sample, *I, j* represents the current input and the neuron sequence number of the current fuzzy layer, respectively.

$$f_2(i, j) = g(f_1(i), c_{ij}, \sigma_{ij}), g(r^2) = \exp(-\frac{r^2}{2\sigma^2}) \tag{3}$$

The third layer is the defuzzification layer. In order to reflect the time coupling characteristics of the time input parameters, it is necessary to reflect the delay effect in this neuron. By selecting the motion input at the corresponding time delay order and low-precision aerodynamic neurons, and multiplying the corresponding neuron output, the effects of aerodynamics and unsteady motion at a certain delay order at adjacent times are reflected. Among them, *N* represents the corresponding delay order. This layer of neurons reflects the role of the unsteady time-delay effect in the black box model. The reduction of the neuron order is achieved through the defuzzification layer.

$$f_3(j) = \prod_{i=1}^{N} f_2(i, j) \tag{4}$$

2. Surrogate model 2

There are 6 layers of neurons (Subscript Layer1-6) in Agent Model 2, where layer1-3 represents the low-precision aerodynamic data solution process, as shown in Eq. 5. Among them, $\boldsymbol{y}_{LF}{}^T(k)$ refers to the low-precision aerodynamic force obtained by the numerical solution at time ***k***, and ***f*** represents the CFD solution process.

$$\boldsymbol{y}_{LF}{}^T(k), \boldsymbol{y}_{LF}{}^T(k-1), ..., \boldsymbol{y}_{LF}{}^T(k-n) = f_1\left\{ [\boldsymbol{u}^T(k), \boldsymbol{u}^T(k-1), ..., \boldsymbol{u}^T(k-n)] \right\} \tag{5}$$

The input layer of the second layer is inputted by the aerodynamics of the low-precision data of the unsteady solver at the corresponding time. The number of neurons in the input layer is ***n***, where ***n*** represents the delay order.

$$f_2(i) = \left\{ [\boldsymbol{y}_{LF}{}^T(k), \boldsymbol{y}_{LF}{}^T(k-1), ..., \boldsymbol{y}_{LF}{}^T(k-n)] \right\} \tag{6}$$

Layers 3-4 are fuzzy layers, which non-linearly map the input information to achieve data fuzzing. The neural network operation is the same as the surrogate model 1.

$$f_3(i,j) = g(f_2(i), c_{ij}, \sigma_{ij}), g(r^2) = \exp(-\frac{r^2}{2\sigma^2}) \tag{7}$$

$$f_4(j) = \prod_{i=1}^{N} f_3(i,j) \tag{8}$$

3. Surrogate model 3

Agent model 3 is a data fusion layer. This model considers the effects of low-precision data and unsteady motion on the test aerodynamic data at the same time. It solves the weight of the neurons output from the two types of models to the overall output. The fuzzy neural network standard solution process realizes the mapping relationship for unsteady aerodynamic data.

$$y_2(k) = w_0 + \sum_{j=1}^{c} w_j . f_1(j) \tag{9}$$

$$\begin{aligned} y_{HF}(\boldsymbol{x}) = w_0 + \sum_j w_j(\boldsymbol{x}_j) \bullet \prod_i g_{ij}(\boldsymbol{x}_i, \boldsymbol{x}_{i-1}, ..., \boldsymbol{x}_{i-n}, c_{ij}, \sigma_{ij}) + \\ \sum_j w_i(\boldsymbol{x}_i) \bullet \prod_i g_{ij}\left[y^i{}_{LF}(\boldsymbol{x}_i), y^{i-1}{}_{LF}(\boldsymbol{x}_{i-1}), ..., y^{i-n}{}_{LF}(\boldsymbol{x}_{i-n}), c_{ij}, \sigma_{ij} \right] \end{aligned} \tag{10}$$

In this way, the overall data fusion framework can be constructed, which can not only reflect the unsteady and non-linear characteristics of pneumatic data, but also improve the accuracy of CFD calculation results by coupling low-precision pneumatic data. The overall mathematical relationship can be expressed as Eq. 10. It can be seen that the solution of high-precision data is mainly represented by a combination of two models. One class represents the influence of unsteady motion on the aerodynamic results, and the other characterizes the influence of low-precision aerodynamic data on the results. The introduction of low-precision data here reflects the unsteady trend of aerodynamic data, avoids the over-fitting problem caused by the cumulative error effect of the regression model, and improves the adaptability and generalization of small samples of the overall model framework.

C. Model training and hyperparameters optimization

Particle Swarm Optimization (PSO) algorithm is an optimization algorithm proposed by Kennedy and Eberhart [25] in 1995. This method treats the parameters to be optimized as particles, calculates the fitness through particle movement, and gradually iterates to obtain the global optimal solution. PSO optimized neural network is a common method to improve network performance. The complexity and some parameters of the neural network can be adjusted, which makes it suffer from poor stability and inaccuracy. Optimizing the parameters of the neural network through PSO is helpful for accelerating network convergence and quickly locating the optimal value.

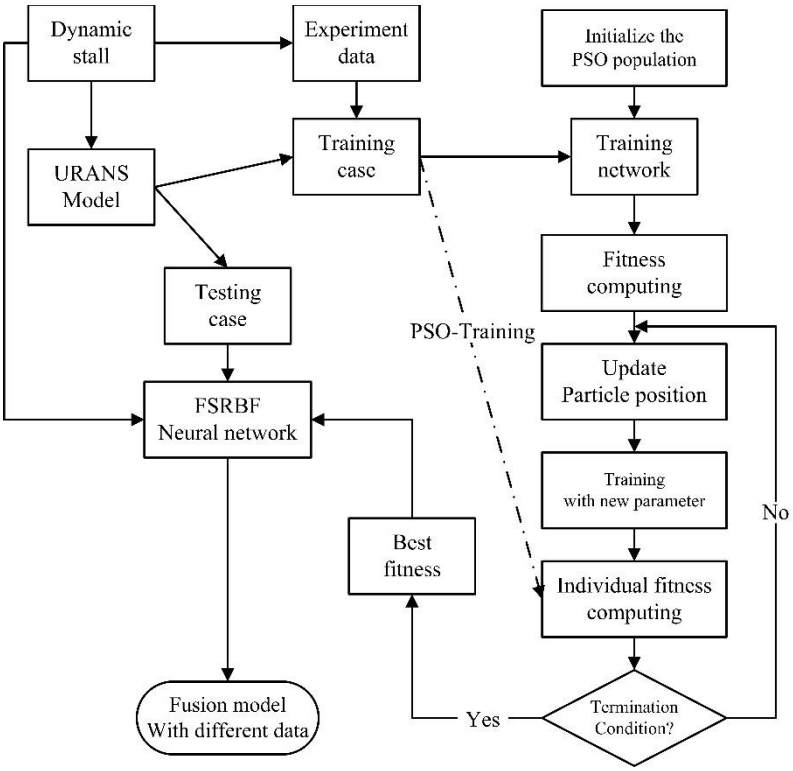


Fig. 4 Data fusion model training and prediction process

Recently, Kou [26] combined with the PSO algorithm to develop an aerodynamic modeling method with verification signals, and enhanced the generalization ability of aerodynamic ROM. This paper also uses this optimization algorithm, combined with data fusion neural network, to implement the neural network model training process with CFD solver nested.

Results

In this section, the proposed data fusion model will be tested. We used very little experimental data to verify the predictive ability of the model for dynamic stall problems. The advantage

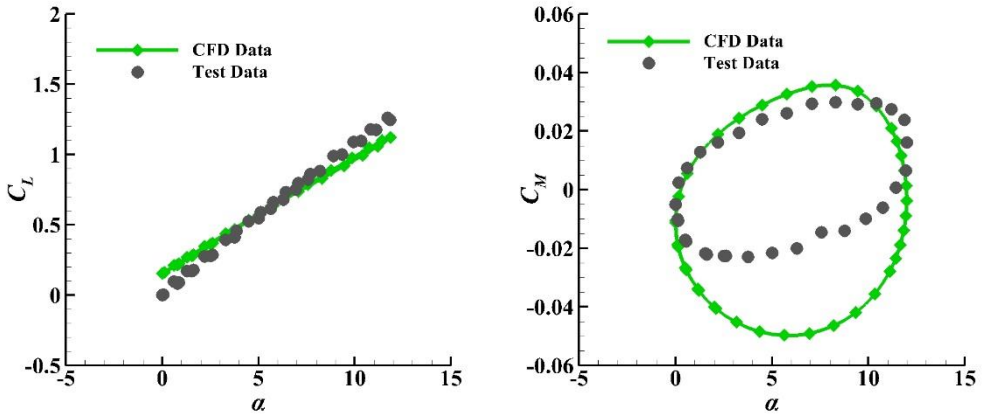
of data fusion is that although it is difficult to conduct a large number of tests for the test data of dynamic stall, only a small amount of test data can be used to build a high-precision model based on numerical simulation methods and black box models to improve the application of test data. At the same time, the confidence of the numerical results can be greatly improved. This part will focus on the training process and application results of the data fusion framework.

A. Training data of data fusion model

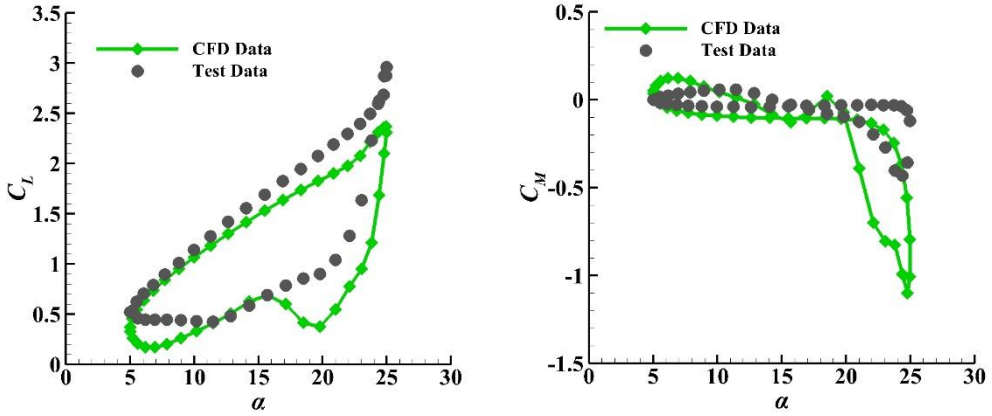
With the support of very few experimental data, three groups of experimental states (A, C, E) were extracted to construct a data fusion model, and the remaining three groups of experimental data (B, D, F) were used to verify the generalization ability of the data fusion framework. During the training process, two sets of experimental data (A, E) are selected as training signals, and the hidden layer center c_{ij} in Eq. 3 is provided. The PSO optimization algorithm is used to find the optimal solution of σ_{ij}. The least squares method is used to solve the weight matrices W_1 and W_2, so that the estimation error of the remaining set of case (C) is minimized. Such a verification training process can effectively improve the generalization ability of the model and avoid overfitting problems [26]. Finally, the delay order n = 5 is selected, and the number of neurons in each layer of the neural network corresponds to 5-10-480-48-2.

In the particle swarm optimization data, the selection range is 0.01-100, the evolution number is 20, and the particle population size is 40. Training data A, E and verification data C are shown in Fig. 8.

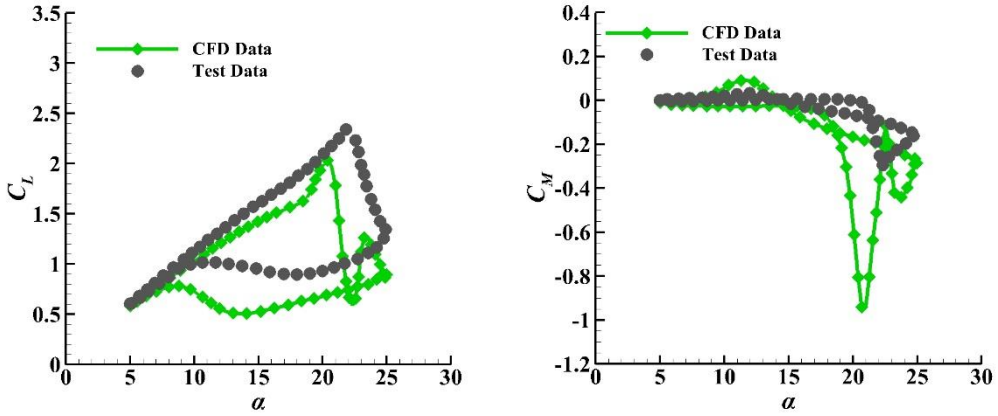
The training signal selection covers the wider aerodynamic boundary as much as possible. The cases with the largest and smallest pitch amplitudes are selected to construct the hidden layer data. The verification signal is used to improve the generalization ability of the sample and avoid over-fitting of small sample data. The aerodynamic data used for prediction not only contains the pitch amplitude and equilibrium angle of attack not included in the training data, but also extrapolates the reduction frequency to test the extrapolation ability of the model.



(a) Training data A：α_0=6°, α_m=6°, *k*=0.15



(b) Training data E：α_0=15°, α_m=10°, *k*=0.2



(b) Training data C：α_0=15°, α_m=10°, *k*=0.05

Fig. 8 Training and validation data of high/low fidelity data

B. Prediction results and errors analysis

We make predictions on the aerodynamic data under B, D, and F test conditions, and check the prediction accuracy against the test data. The error here is the mean square error (MSE), which refers to the mean square error between the predicted data and the experimental data, as shown in Eq. 14.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left|C_f{}^{predicton}(t_i) - C_f{}^{real}(t_i)\right|^2 \tag{14}$$

Fig. 9 shows the prediction result of calculation example F, in which the lift coefficient is compared with the aerodynamic result predicted by the FSRBF neural network model directly trained on the same data and the result of the data fusion algorithm. It can be seen that due to the small sample size of the training data, the direct establishment of the aerodynamic model cannot have a good generalization ability, but instead uses the CFD-nested data fusion model established by the numerical simulation results. Due to the full consideration of the auxiliary role of the low-precision unsteady aerodynamic data, even a small test sample can make the black box model capture the conversion characteristics between data well. In addition, a low-fidelity aerodynamic data model is used to obtain high prediction accuracy. Even with more complex moment coefficients, the CFD-nested data fusion framework also shows high prediction capabilities.

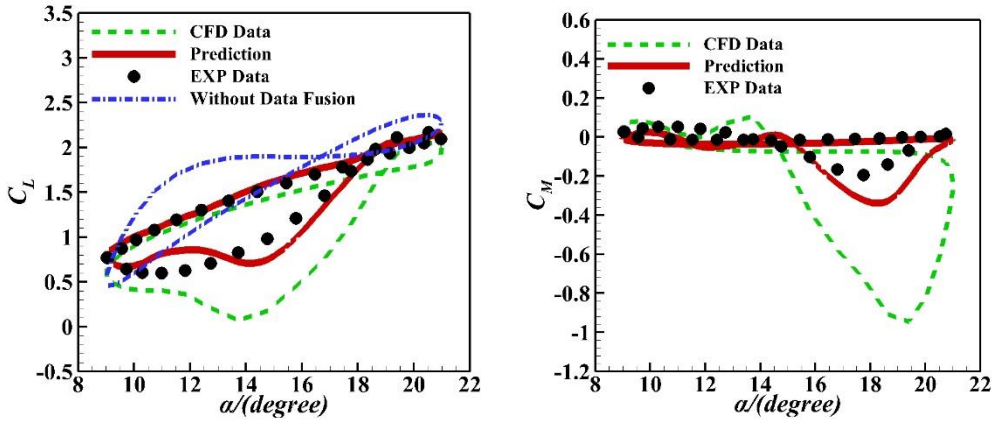


Fig. 9 Test case F： α_0**=15°,** α_m**=6°,** ***k*****=0.24**

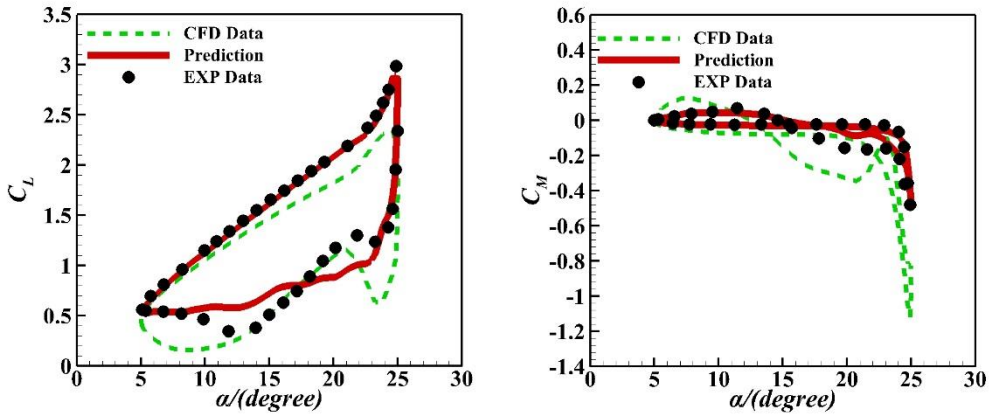


Fig. 10 Test case D： α_0=15°, α_m=10°, *k*=0.15

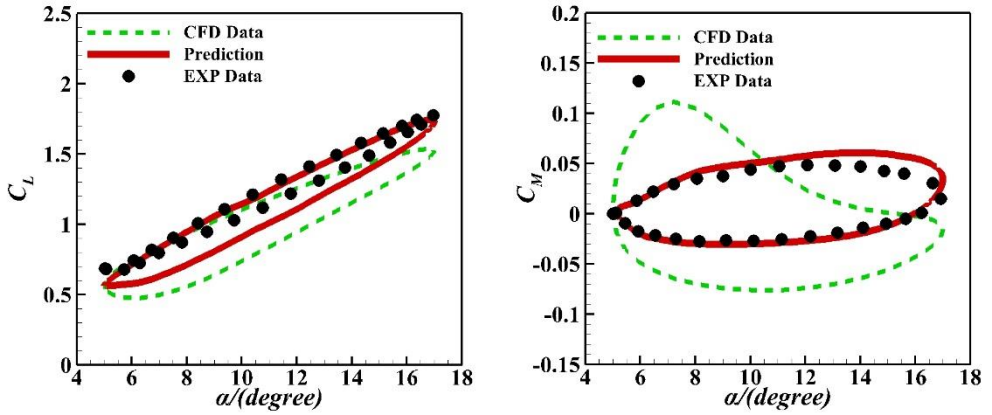


Fig. 11 Test case B： α_0=11°, α_m=6°, *k*=0.24

Fig. 10 and Fig. 11 show the comparison of data fusion prediction aerodynamic coefficients with experimental aerodynamic data. It can be seen that 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 a large number of 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.

Considering the comparison of the prediction errors of the models, Table 2 shows the comparison of the prediction errors of the various examples. Under the results of model training, the model obtains smaller prediction errors under different equilibrium angles of attack, pitch amplitudes, and reduction frequencies. Compared with the numerical simulation results, the prediction data error is reduced by 2-3 times, which proves the generalization ability and model accuracy of the model.

Table 2. Mean square errors comparison of CFD method and data fusion method

Test case	MSE			
	CFD C_L	Prediction C_L	CFD C_M	Prediction C_M
Case d	0.0528	0.0150	0.0491	0.0096
Case e	0.0446	0.0169	0.0290	0.0057
Case f	0.0351	0.0143	0.0073	0.0015

C. Model convergence analysis

In the previous section, we verified the generalization ability of the aerodynamic coefficients under dynamic stall conditions with the data fusion framework nested with the CFD solver under a small number of training samples. Next, continue to study the impact of increasing training data on model accuracy. Considering that the training data reflects the conversion relationship between the numerical simulation data and the experimental data, more training samples should better improve the prediction accuracy of the experimental data. If the accuracy does increase with the increase of sample data, then the accuracy convergence of the model will be proved, and the auxiliary modeling role of data fusion will be reflected.

For three prediction examples, non-predicted aerodynamic data is added to the training examples as training samples to optimize the data fusion model. In the three sets of traditional prediction models modeled, To establish a data fusion model using the remaining 5 samples as training signals, to investigate the model's convergence with increasing training samples.

Fig. 12 to Fig. 14 show the prediction results of model with a lager training set. In the figure, Prediction 1 represents the modeling results of a small amount of training data, and Prediction 2

represents the prediction results from model with a large training set. It can be seen from Table 3 that the model prediction error is further reduced compared to section 3.2, which fully demonstrates the model's convergence to the training data. Compared with a small sample model, the model's prediction accuracy can be obtained with more certain test data.

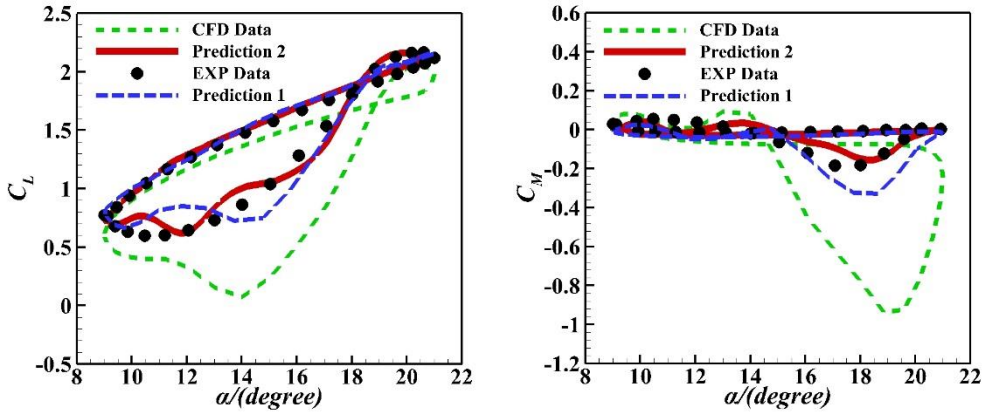


Fig. 12 Test case F： α_0**=15°,** α_m**=6°,** ***k*****=0.24**

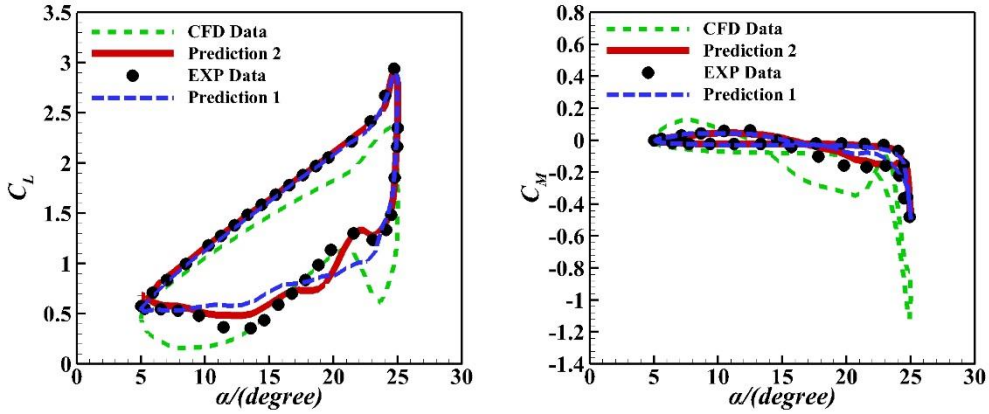


Fig. 13 Test case D： α_0**=15°,** α_m**=10°,** ***k*****=0.15**

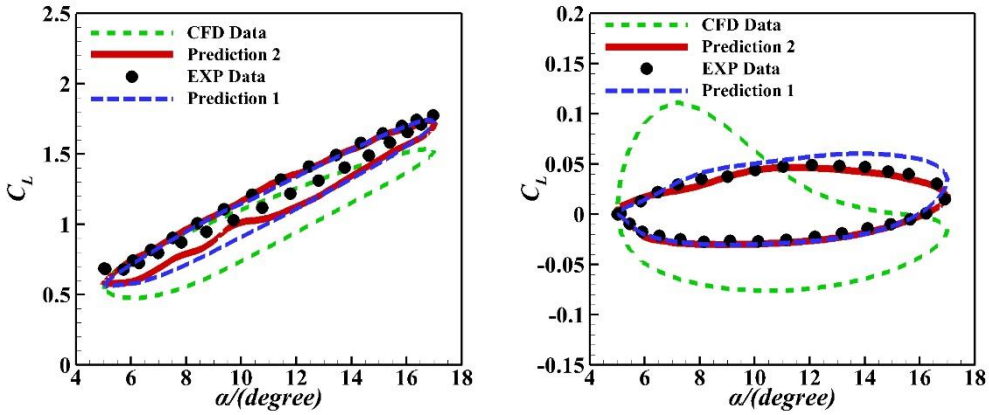


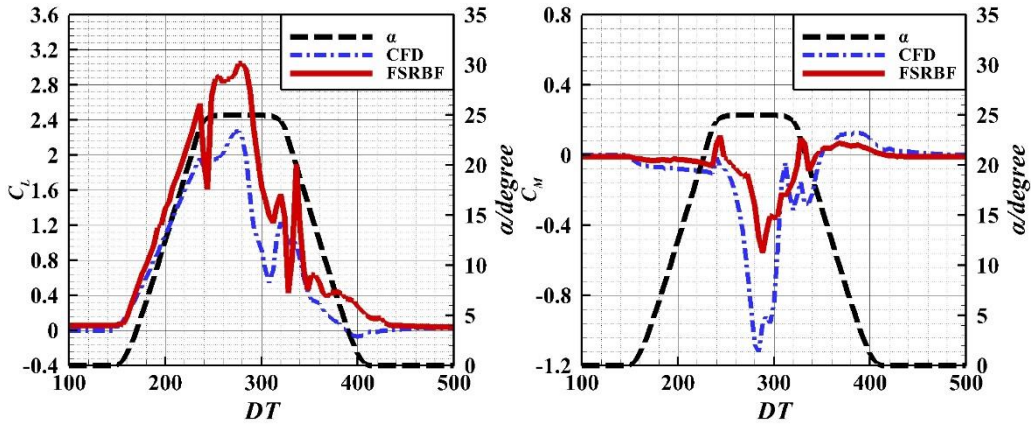
Fig. 14 Test case B： α_0**=11°,** α_m**=6°,** ***k*****=0.24**

Table 3. Mean square error comparison between two prediction examples

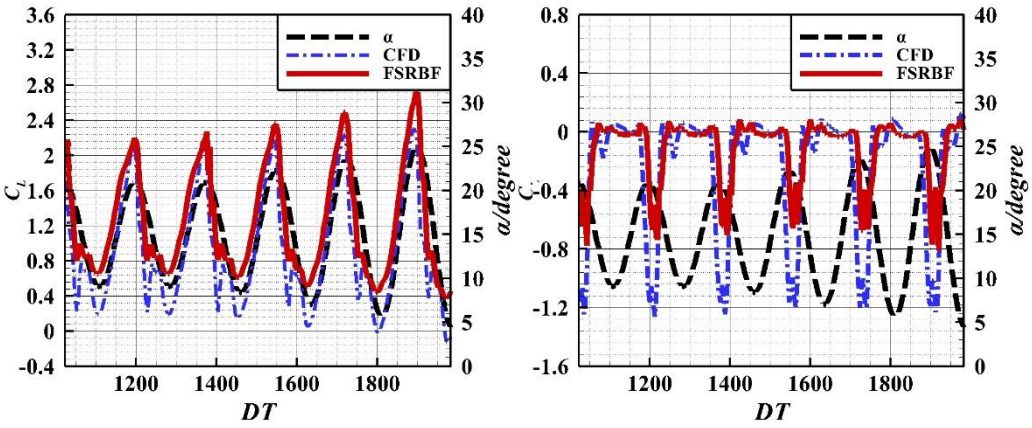
Test case	MSE			
	Prediction1 C_L	Prediction 2 C_L	Prediction 1 C_M	Prediction 2 C_M
Case d	0.0150	0.0102	0.0096	0.0047
Case e	0.0169	0.0125	0.0057	0.0043
Case f	0.0143	0.0118	0.0015	0.0006

D. Time-domain prediction examples of dynamic stall

The framework based on data fusion not only has a good prediction ability for dynamic stall problems of simple harmonic motion. Because the design of the model is not constrained by the form and state of motion, the data fusion framework can also predict aerodynamic forces in any periodic and aperiodic motion. Next, the two sets of aerodynamic prediction results under non-harmonic motion are shown. Although there is no comparison of experimental results for the dynamic stall problem of non-periodic motion, it can be estimated that compared with the results of the unsteady dynamic stall obtained by numerical algorithms, The prediction results have higher confidence and are closer to the actual experimental data. From the comparison of lift and moment coefficients, it can be seen that although the model fusion results are similar to a certain extent, there is still a clear correction in amplitude and trend from the CFD results.



(a) Non-harmonic square wave signal prediction results



(b) Simple harmonic divergence signal prediction result

Fig. 15 Comparison of prediction results of unsteady aerodynamic data

3. Conclusion

This paper proposes a data fusion and fusion modeling method for dynamic stall problems, and uses the data fusion method to establish an aerodynamic prediction model for airfoil dynamic stall. With the support of a small amount of experimental data, the model can be combined with the low-precision aerodynamic data calculated by the numerical simulation of the unsteady RANS model to correlate the numerical results with the aerodynamic data of the dynamic stall test. By designing the integrated neural network model of the nested unsteady solver, the nonlinear and unsteady modeling process of aerodynamic data is realized. Aiming at the problem of poor accuracy of numerical simulation data and the difficulty of directly modeling the experimental data volume, the data fusion method is used to consider the combination and transformation relationship between the data. The integrated fuzzy neural network is used to implement the dynamic stall aerodynamic data. Precise capture and high accuracy. The model can play a key role in predicting aerodynamics in the range of angle of attack and reduced frequency that are difficult to perform by experimental means. Finally, by strengthening the training set, the convergence of the model is verified, and the accuracy of the model is improved. The advantages of data fusion modeling methods for nested unsteady solvers can be summarized as three points:

1. An unsteady aerodynamic integrated data fusion modeling approach is proposed, which can effectively utilize neural network features and a low-precision solver to implement model generalization and extrapolation.

2. This method can use the simulation data and a small number of experimental results to improve

the prediction of experimental results and save costs.

3. Compared with a single data source recursive model, it can avoid the problem of error accumulation in the recursive model and improve the generalization ability of the model itself.

Further work may consider using data fusion methods for high-fidelity virtual flight design and simulation of aeroelastic problems based on experimental data.

Copyright Statement

References

[1] Shyy, Wei, et al. "Recent progress in flapping wing aerodynamics and aeroelasticity." *Progress in Aerospace Sciences* 46.7 (2010): 284-327.

[2] SureshBabu, ArunVishnu, Kiran Ramesh, and Ashok Gopalarathnam. "Model reduction in discrete-vortex methods for unsteady airfoil flows." *AIAA Journal* 57.4 (2019): 1409-1422.

[3] Ekaterinaris, John A., and Max F. Platzer. "Computational prediction of airfoil dynamic stall." *Progress in aerospace sciences* 33.11-12 (1998): 759-846.

[4] Young, John, and Joseph C. S. Lai. "Oscillation frequency and amplitude effects on the wake of a plunging airfoil." *AIAA journal* 42.10 (2004): 2042-2052.

[5] RS, D. Surekha, A. Khandelwal, and R. Rajasekar. "Investigation of Flow Field in Deep Dynamic Stall over an Oscillating NACA 0012 Airfoil." *Journal of Applied Fluid Mechanics* 12.3 (2019).

[6] Jain, Rohit, et al. "High-resolution computational fluid dynamics predictions for the static and dynamic stall of a finite-span OA209 wing." *Journal of Fluids and Structures* 78 (2018): 126-145.

[7] McAlister, Kenneth W., Lawrence W. Carr, and William J. McCroskey. "Dynamic stall experiments on the NACA 0012 airfoil." (1978).

[8] Holierhoek, J. G., et al. "Comparing different dynamic stall models." *Wind Energy*,16.1 (2013): 139-158.

[9] Tran, C. T., and D. Petot. "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." (1980).

[10] Leishman, J. Gordon, and T. S. Beddoes. "A Semi‐Empirical model for dynamic stall." *Journal of the American Helicopter society* 34.3 (1989): 3-17.

[11] Gangwani, Santu T. "Prediction of dynamic stall and unsteady airloads for rotor blades." *Journal of the American Helicopter Society* 27.4 (1982): 57-64.

[12]DeLaurier, James D. "An aerodynamic model for flapping-wing flight." *The Aeronautical Journal* 97.964 (1993): 125-130.

[13]Kim, Dae-Kwan, Jun-Seong Lee, and Jae-Hung Han. "Improved aerodynamic model for efficient analysis of flapping-wing flight." AIAA journal 49.4 (2011): 868-872.

[14]Zhang, W., and Ye, Z., “Reduced-Order-Model-Based Flutter Analysis at High Angle of Attack,” Journal of Aircraft, Vol. 44, No. 6, 2007,pp. 2086–2089.

[15]Kurtulus, Dilek Funda. "Ability to forecast unsteady aerodynamic forces of flapping airfoils by artificial neural network." *Neural Computing and Applications* 18.4 (2009): 359.

[16]Winter, Maximilian, and Christian Breitsamter. "Neurofuzzy-model-based unsteady aerodynamic computations across varying freestream conditions." *Aiaa Journal* (2016): 2705-2720.

[17]Navon, Ionel M. "Data assimilation for numerical weather prediction: a review." *Data assimilation for atmospheric, oceanic and hydrologic applications*. Springer, Berlin, Heidelberg, 2009. 21-65.

[18]Ghoreyshi, Mehdi, K. J. Badcock, and M. A. Woodgate. "Accelerating the numerical generation of aerodynamic models for flight simulation." *Journal of Aircraft* 46.3 (2009): 972-980.

[19]Kou, Jiaqing, and Weiwei Zhang. "Multi-fidelity modeling framework for nonlinear unsteady aerodynamics of airfoils." *Applied Mathematical Modelling* 76 (2019): 832-855.

[20]Parish, Eric J., and Karthik Duraisamy. "A paradigm for data-driven predictive modeling using field inversion and machine learning." *Journal of Computational Physics* 305 (2016): 758-774.

[21]Wang, Jian-Xun, Jin-Long Wu, and Heng Xiao. "Physics-informed machine learning approach for reconstructing Reynolds stress modeling discrepancies based on DNS data." *Physical Review Fluids* 2.3 (2017): 034603.

[22]M. Giselle Fernández-Godino, C. Park, N.H. Kim, R.T. Haftka, Review of Multi-fidelity Models, (2016) eprint arXiv:1609.07196.

[23]Chen, S., et al. "Non-linear systems identification using radial basis functions." *International Journal of Systems Science* 21.12 (1990): 2513-2539.

[24]Xu Wang, Jiaqing Kou, and Weiwei Zhang. "Unsteady aerodynamic modeling based on fuzzy scalar radial basis function neural networks." *Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering* (2019): 0954410019836906.

[25]Eberhart, Russell, and James Kennedy. "A new optimizer using particle swarm theory." Micro Machine and Human Science, 1995. MHS'95., Proceedings of the Sixth International Symposium on. IEEE, 1995.

[26]Kou, Jiaqing, and Weiwei Zhang. "An approach to enhance the generalization capability of nonlinear aerodynamic reduced-order models." *Aerospace Science and technology* 49 (2016): 197-208.

[27]De Boer, A., M. S. Van der Schoot, and Hester Bijl. "Mesh deformation based on radial basis function interpolation." *Computers & structures* 85.11-14 (2007): 784-795.

[28]Jiang, Y. "Numerical solution of Navier–Stokes equations on generalized mesh and its applications." *NWPU, Xi’an, China (Ph. D. thesis)* (2013).

[29]Zhang, Weiwei, et al. "Mechanism of frequency lock-in in vortex-induced vibrations at low Reynolds numbers." *Journal of Fluid Mechanics* 783 (2015): 72-102.

[30]Gao, Chuanqiang, et al. "Mechanism of frequency lock-in in transonic buffeting flow." *Journal of Fluid Mechanics* 818 (2017): 528-561.