FAST PREDICTION OF PRESSURE DISTRIBUTION FOR 3D CONFIGURATION BASED ON LARGE LANGRAGE MODEL

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Abstract

Computer Fluid Dynamics (CFD) has become an important method of aircraft design. With the improvement of aircraft performance, the contradiction between accuracy and efficiency of numerical simulation becomes more and more obvious. In this paper, a deep learning framework based on large langrage model Bert” is proposed for predicting pressure and velocity distributions for 3D configurations. Based on our framework, the pressure and velocity distribution can be obtained quickly by inputting the aircraft shape points and incoming flow conditions. The proposed framework avoids the influence of computational grid on neural network model, and can use any CFD or experimental results for training. The transonic states of 500 shapes are calculated by Euler equation as inputs of neural network, of which 400 are used for training and 100 are used for testing. The results show that our method can accurately predict the surface pressure and velocity distribution of aircraft, and the time consumption is only seconds, thus achieving a win-win situation of accuracy and efficiency. Our framework is suitable for arbitrary CFD methods and experimental data, and avoids the dependence of neural networks on computational grids

Keywords: deep learning, pressure prediction, aerodynamics, large langrage model

1. Introduction

With the rapid development of computer technology, computational fluid dynamics (CFD) has become an important method of aircraft design[1]. In aircraft design, researchers generally pay attention to the force coefficient integrated by surface pressure or friction distribution[2]. In order to get the force coefficient accurately, it is necessary to adopt carefully designed grid and accurate calculation method. In complex flow areas, it is necessary to increase grids to get good results. In recent years, CFD-based aerodynamic and multidisciplinary optimization has attracted the attention of researchers, which requires repeated use of CFD to solve the flow field. Fine design leads to the unbearable computation of repeatedly calling CFD. Even if the surrogate optimization method is adopted, it will face the problem of "dimension curse"[3][4]. How to deal with the accuracy and efficiency of CFD has become the key problem restricting aircraft design.

In recent years, the rapid development of artificial intelligence, especially deep learning, provides a new way to solve the problem of CFD efficiency and accuracy. In fluid mechanics modeling and prediction, deep learning technology has great application prospects. "Universal approximation properties"[5] points out that a feedforward neural network satisfying certain conditions can approximate Borel measurable functions with arbitrary accuracy as long as a sufficient number of hidden elements are given. Because most functions in practical application satisfy the conditions stated in this theorem, the feasibility of deep learning of flow field has been firmly guaranteed in theory. On the other hand, the existing CFD method has obtained a large amount of data, which is a good platform for the application of deep learning technology. In the field of flow field prediction and aerodynamic design, data-driven models based on a large number of existing data have been widely studied, and convolution neural network (CNN) is one of the most popular approaches. Sekar et al.[6][7] processed the input airfoils into pixelated images and employed CNN for airfoil flow field prediction and inverse design, and the trained network achieved good prediction accuracy even on unseen airfoils. Thuerey et al[8]. also used CNN to simulate the airfoil flow. The influence of network parameters and sample size on the training results were studied, and the relative error of predicted pressure field was less than 3% on the unseen airfoils. Balla et al[9]. proposed a multi-ouput neural network for aerodynamic coefficients of airfoils in two dimensions and wings in three dimensions. Duru et al[10]. proposed an encoder-decoder neural network model (CNN-FOIL) to predict transonic flow field around airfoils and got good performance. Wu et al[11]. designed generative adversarial network (GAN) with CNN structure to predict the flow fields of supercritical airfoils. Hu et al[12]. transformed the non-uniform physical plane into a uniform computational plane through coordinate transformation, and carried out the flow field simulation of airfoils and simple wings based on CNN, which further broadened the applicable scope of CNN model in flow field prediction. Yang et al[13]. used varaitional autoencoder to generate new flowfields of airfoils under different conditions.

All these studies have proved that deep learning has great potential in flow field prediction, but these studies mainly focus on two-dimensional airfoils or simple wings, and these methods depend on grids (mostly Cartesian grids or structured grids), which restricts their application in three-dimensional complex configurations. Shen et al[14]. proposed a deep learning framework based on pointnet++ to get pressure on three-dimensional configurations. However, this method has not been verified in complex flow. Hines D et al[15]. used a graph neural network approach to predict surface pressure distributions of aircraft, this method got good performance for complex cases involving several hundreds of thousands of nodes. The emergence of transformer architecture[16] in 2017 made a breakthrough in the field of deep learning. Subsequently, based on this architecture, new models suitable for natural language processing and computer vision, such as Bert[17], Chatgpt and Vision-transformer[18], appeared one after another, bringing deep learning research to a new height. Using the powerful feature extraction ability of transformer architecture and based on bert model we realized the prediction of aircraft surface flow field which is not limited by grid type and suitable for three-dimensional complex configuration. The results show that our method can accurately predict the transonic flow field of different flying wing configurations within 5 seconds, and accurately capture the shock wave intensity and shock wave position

2. Methodology

2.1 Shape generation

On the basis of the baseline shape, this section aims to generate a dataset with a variety of shapes by the parametric approach. The baseline flying wing is shown as Figure 1. Specific parameters are shown in Table 1. The advanced geometric modeling and CFD evaluation software OPENVSP is used for geometric parameterization. Compared with free form deformation method which controls the change of coordinate points, OPENVSP realizes the shape generation and deformation of aircraft by specifying physical variables such as airfoil, sweep angle, root chord length and spread length, which has physical significance and is not easy to generate unreasonable shape.

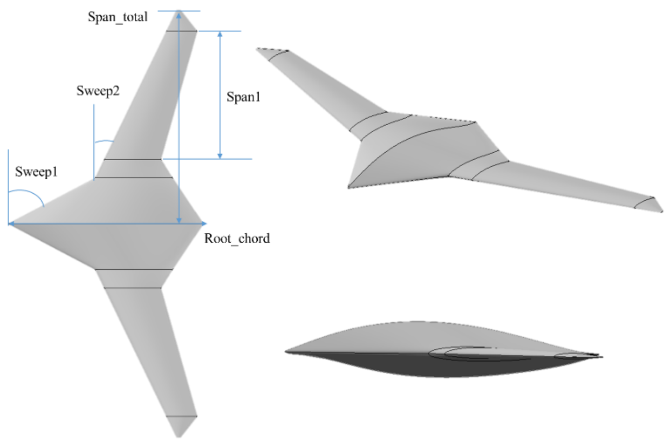


Figure 1 -Geometry of baseline flying wing

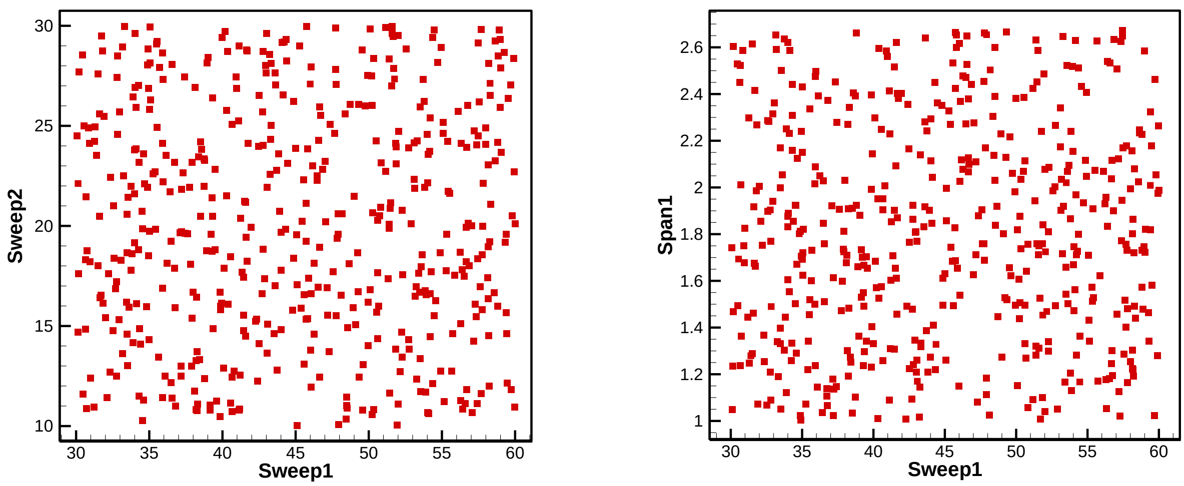
Table 1 Geometry parameters of baseline flying wing

Sweep1	Sweep2	Root_chord	Span1	Span_total
55°	20°	3.85m	3.36m	5.6m

When the new configuration is generated, the inner wing sweep angle Sweep1, the outer wing sweep angle Sweep2 and the outer wing half span Span1 are selected as parameterized variables, keeping the airfoil profile and other parameters unchanged. 500 samples are randomly generated by Latin Hypercube method, and the range of each parameter is shown as Table 2. Figure 2 gives the distribution of each parameter. It can be seen that the distribution of each parameter accords with random distribution, which proves the rationality of sampling.

Table 2 Parameter value range

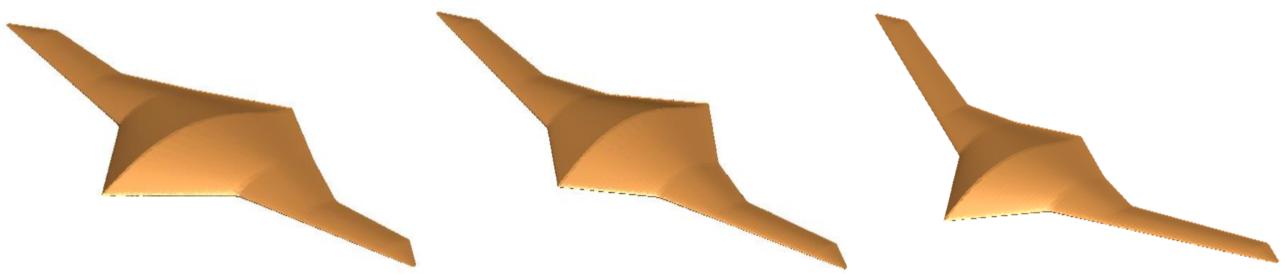
	Baseline	Deform range
Sweep1	55°	[30°, 60°]
Sweep2	20°	[10°, 30°]
Span1	3.36m	[1m, 2.75m]



(a) Sweep1 vs Sweep2 (b) Sweep1 vs Span1

Figure 2 -Parameter distribution

The shapes of some samples are shown as Figure 3, and it can be seen that the shape after deformation is smooth and conforms to the aircraft design criteria, which proves the effectiveness of the parametric method.



(a) Sample1 (b) Sample2 (c) Sample3

Figure 3 -Shapes of different samples

2.2 CFD simulation

In this work, 500 cases are generated as the dataset Considering that the three-dimensional problem requires large sample size and the numerical solution of RANS equation takes a long time, we use Cartesian grid solver to solve Euler equation, and get the surface pressure distribution of different samples. By solving the Euler equations for numerical simulation, we can obtain nonlinear flow characteristics such as shock wave and ensure high computational efficiency. The Euler equations can be expressed as follows:

$$\begin{aligned} &\nabla \bullet (\rho \boldsymbol{u}) = 0 \\ &\nabla \bullet (\rho \boldsymbol{u}\boldsymbol{u}) + \nabla p = 0 \\ &\nabla \bullet (\rho \boldsymbol{u} E) = 0 \end{aligned} \tag{1}$$

$$E = \frac{1}{2}|\boldsymbol{u}|^2 + \frac{\gamma}{\gamma - 1}\frac{p}{\rho} \tag{2}$$

Where u denotes the velocity, ρ and p denote density and pressure, respectively. E denotes the total energy per unit mass. The air is treated as an ideal gas, thus, γ is 1.4. For time advance, the implicit Lower-Upper Symmetric Gauss-Seidel scheme is used to solve the Euler equations and the Courant-Friedrichs-Lewy (CFL) number is 100. In order to further improve the efficiency, Cartesian grid is adopted as the computational grid. In all the calculations, the surface grid size of the flying wing is about 50000, and the calculated states are shown in Table 3. At this condition, there is shock wave s on the aircraft surface, which further tests the accuracy of our method. Because the purpose of this paper is to verify the method, the accuracy of CFD solver has not been studied in detail. Figure 4 shows the convergence history of sample 1. After 800 CFD iterations, the lift or drag coefficient converges basically, which can be used for neural network training.

Table 3 Inflow conditions

Ma	Angle of attack	Angle of sideslip
0.85	3°	0°

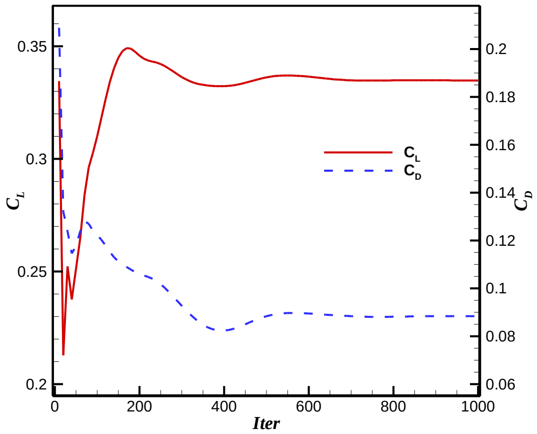


Figure 4 -Convergence history for sample1

2.3 Bert model

Bert model is based on transformer architecture, including pre-training and fine-tuning. In NLP, Bert model is excellent in cloze problem because it trains a depth bidirectional model. Bert's success also shows that deep learning is representational learning, and we can fine-tune parameters according to different downstream task requirements on the pre-training model to achieve the desired results. Therefore, on the basis of Bert model, we have carried out the work of predicting the pressure distribution of three-dimensional configuration. The transformer architecture is shown in Figure 5. Wherein, the left half is an encoder and the right half is a decoder. We can use the entire Transformer architecture as needed, or we can use the encoder or decoder section alone.

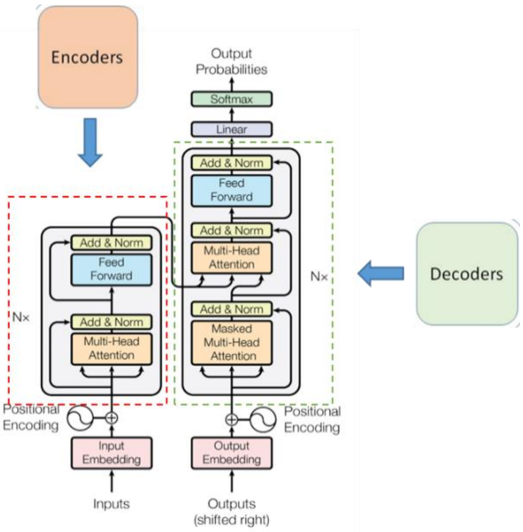


Figure 5 -The transformer architecture

Bert model can be regarded as the encoder part of Transformer, that is, we can use Bert model to extract features. In this paper, we use Bert Base model, whose parameters are about 110 million. The Bert model diagram is shown in Figure 6. Specific details about the Bert model can be found in reference [17].

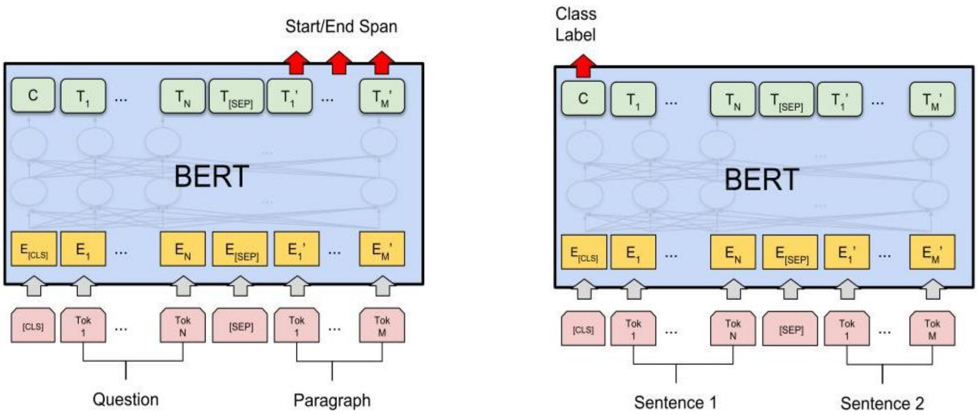


Figure 6 -Bert model

Figure 7 shows the concrete steps of the proposed model. In the training process, CFD evaluation is carried out on the generated shape at first. Then the grids and the corresponding surface pressure distribution are tokenized and input into Bert model, where the surface pressure distribution is used as the label value. After Bert model, the output results are logistically regressed, and finally the predicted surface pressure distribution is obtained. When predicting, the corresponding surface pressure distribution can be obtained by inputting the coordinate points of the new shape.

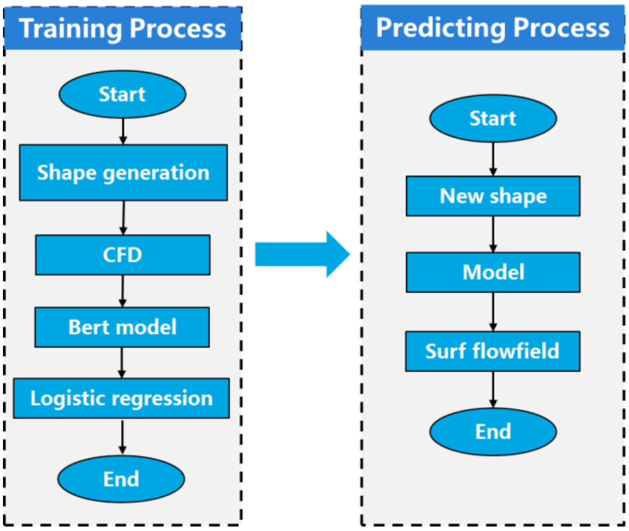


Figure 7 -Model diagram

3. Results and Discussion

Since the number of coordinate points of different shapes is not the same, we unify the number of coordinate points of different shapes to 60,000 (greater than the number of coordinate points of the shape itself). When the outline coordinate points are less than 60000, we randomly extract some coordinate points from the coordinate points to supplement. Adaptive momentum estimation optimization algorithm is used as the optimizer during the training process, and the learning rate is 0.001. The MSEloss in PyTorch is used as the loss function, and the maximum training epoch is set to 100. Since a total of 500 CFD cases have been solved, the dataset is randomly divided into a training set (400), and a test set (100) in this study. In the training process, the results of the new round will be compared with the results of the previous round. If the loss function decreases, the current model will be saved, so as to ensure that the saved model after reaching the maximum epoch is the best model. The training of the model is performed on the GPU of Nvidia Tesla A100.

The convergence history of the training set and the test set is shown in Figure 8. The initial loss function value of the training set and the test set is around 0.02. After 100 epch training, the loss function value of the best model on the training set and the test set is around 0.0003, which is two orders of magnitude lower than the initial value.

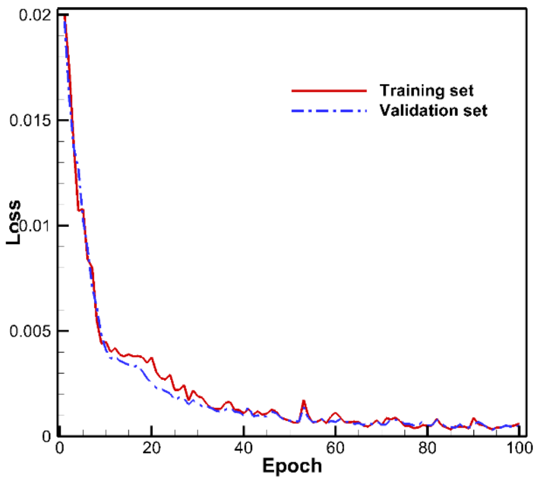


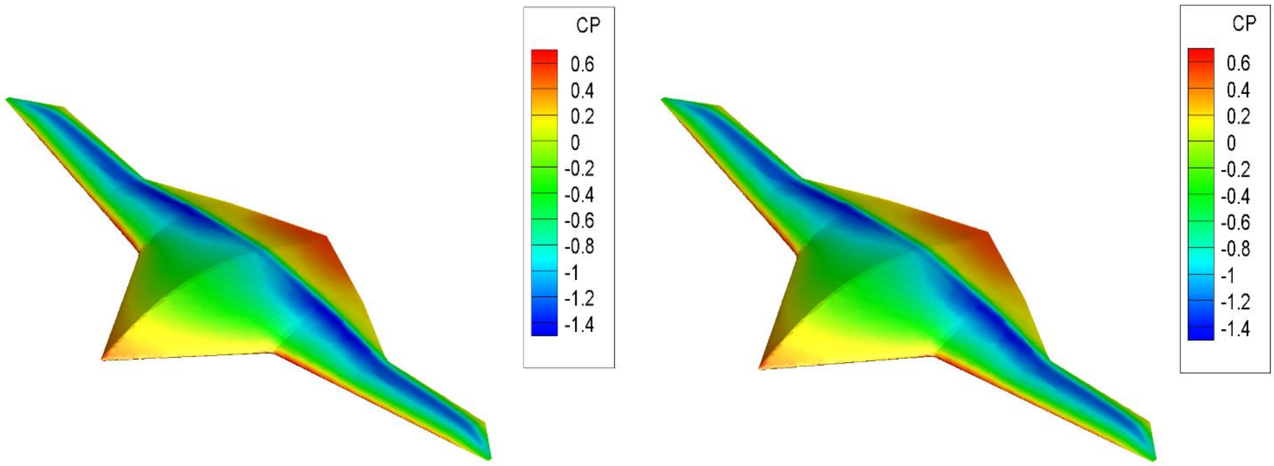
Figure 8 -Convergence history

In order to quantify the accuracy of the model prediction, R-square is used to characterize the consistency between the predicted velocity and pressure distribution and CFD calculation results. The R-squre can be seen in Table 4. It can be seen that in addition to the velocity w along the spanwise direction of the aircraft, the R-square value of other velocity components exceeds 0.99, and the R-square value of the surface pressure coefficient reaches 0.999, which proves that the model has good fitting ability.

Table 4 R-square for prediction

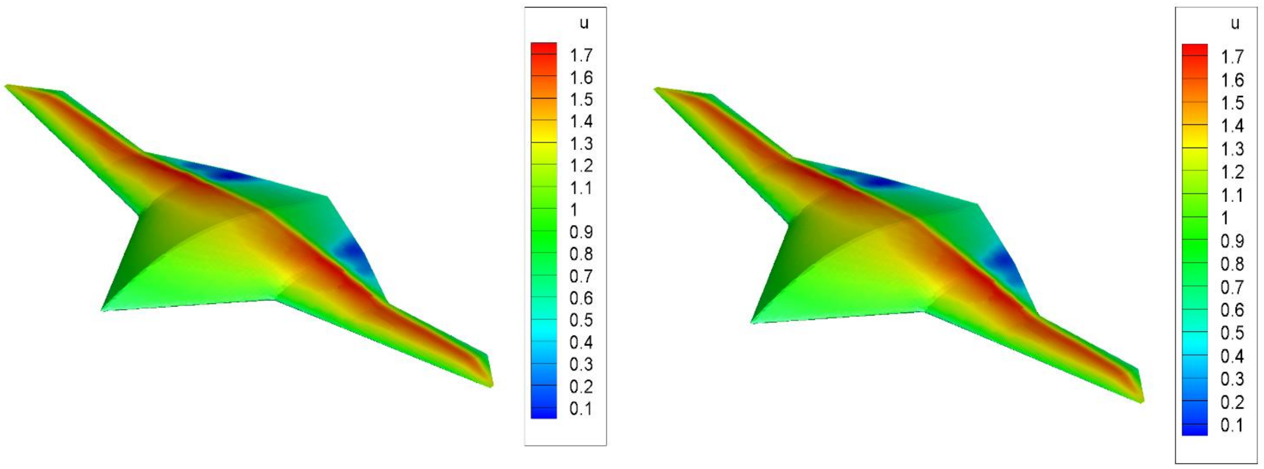
	Cp	u	v	w
R-square	0.999	0.994	0.987	0.997

Figure 9 and Figure 10 show the comparison of model predicted values and CFD values for the contour surface pressure distribution and X-direction velocity distribution in the test set. It can be seen that in the test set, there are obvious shock waves on the surface of the aircraft under the condition of transonic velocity. The model accurately predicted the surface pressure distribution and velocity distribution, and predicted the shock wave position and intensity.



(a) Prediction (b) CFD

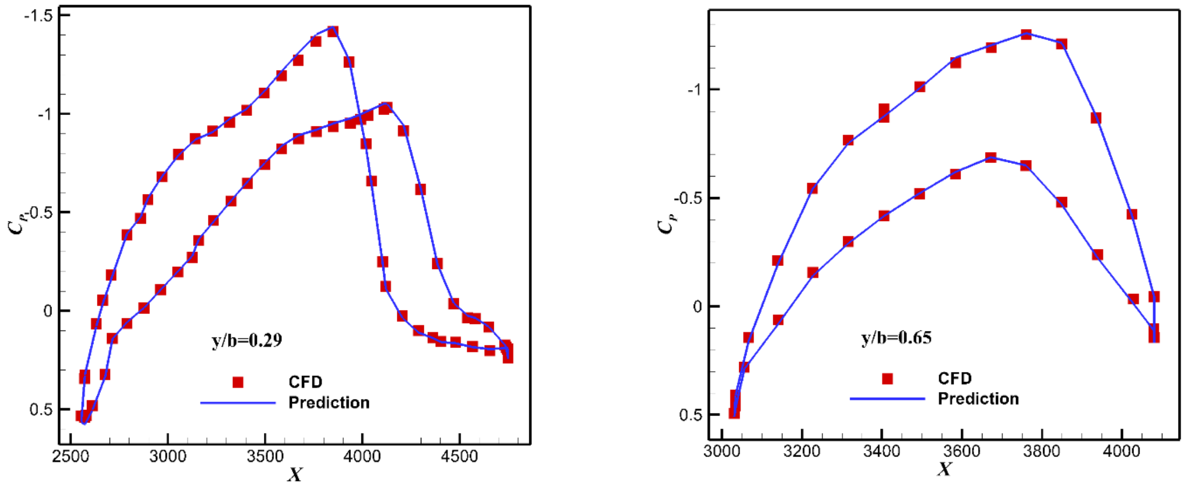
Figure 9 -Pressure coefficient comparison from validation set



(a) Prediction (b) CFD

Figure 10 -U velocity comparison from validation set

Figure 11 gives the comparison between the pressure distribution predicted by the model and CFD calculation results at different locations along the spanwise. It can be seen that the shock position predicted by the model is very consistent with the shock position calculated by CFD and the peak pressure. When there is no shock wave on the surface, the pressure predicted by the model is almost consistent with the CFD calculation result.



(a) y/b=0.29 (b) y/b=0.65

Figure 11 -Pressure coefficient comparison for different location

4. Conclusions

1) The framework proposed in this paper can accurately predict the surface pressure distribution and velocity field of 3D configuration at transonic conditions. The method in this paper only needs seconds to predict a state, which greatly improves the efficiency compared with traditional CFD methods.
2) The method in this paper only needs grid points or geometric modeling points as inputs, and has the potential to predict multiple physical fields, so it has strong applicability and extensibility.

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6. Copyright Statement

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