DEEP LEARNING BASED FAST PREDICTION OF AERODYNAMIC PARAMETERS FOR DUCTED PROPELLERS

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Abstract

Ducted propellers are widely used in eVTOL and the shape of the duct has a significant impact on aerodynamic performance. In the traditional design process, the method of obtaining the aerodynamic performance of ducted propeller is CFD, which is very costly. In this work, a deep learning based method for aerodynamic performance prediction of ducted propellers is proposed, which can predict the aerodynamic performance within 0.06s under different shapes and working conditions, reduce calculation consumption greatly. Two neural networks based on optimal network structures, the DNN and the Optimized Network, are used to build surrogate models and compared in this paper. The training results show that the Optimized Network is more advantageous in terms of prediction precision. For this problem, neural network surrogate model is more interpretable and performs better than traditional surrogate models, such as response surface model and Kriging model.

Keywords: surrogate model; deep learning; ducted propeller; computational fluid dynamics method; optimization.

1. Introduction

Ducted propellers are widely used in Electric Vertical Take-off and Landing (eVTOL) as a new type of thrust component. The shape of the duct plays an important role in the aerodynamic performance of the ducted propeller, which needs to be taken into account during the design process. The traditional design method is to manually apply small disturbances to the external shape and obtain performance parameters through CFD numerical simulation, and evaluate the quality of the design by comparing the aerodynamic performance. By repeating the above process several times, the optimal design solution can be selected. The method of obtaining aerodynamic performance through numerical simulation has high precision, but the simulation cycle is long and consumes a lot of computational resources. In the future, duct design should consider more design constraints, and the scale of design variables is also expanding. If only high-precision CFD method is applied in the ducted propeller design, it is time-consuming to explore the high-dimensional variable space and finding the optimal design solution is extremely difficult.

Considering both efficiency and global search capability, the surrogate-based aerodynamic performance prediction method emerges in the aircraft design[1]. Surrogate models built with limited CFD sample data can achieve mapping between shape and aerodynamic performance in a short period of time, enabling fast aerodynamic performance prediction. At present, response surface[2], Kriging model[3], and data-driven neural network[4] have been developed. However, for most aerodynamic prediction models based on surrogate method, all input features are considered equivalent and input into the model at once, which leads to different physical features that cannot be fully explored, resulting in unsatisfactory prediction results. The inner physical properties of each feature, as well as their relationship, are ignored. These prediction models are difficult to interpret as well. Data-driven neural network is a new product that has certain advantages over traditional surrogate model. Users can build their own network structure based on their own needs and the characteristics of the dataset, in order to fully explore the interaction relationship between input parameters and improve the predictive performance of the surrogate model.

In the current study, a deep learning based surrogate model is developed for the aerodynamic prediction of ducted propellers, which could solve the above-mentioned drawbacks of traditional surrogate models. This surrogate can combine different physical properties to improve the prediction precision, and has a certain generalization ability and interpretability. Current work incorporates significant innovation. The inclusion of feature extraction and multi-task learning allows the neural network surrogate model to effectively fuse geometry, flight conditions and flow field information. This higher-order fusion method makes the model more interpretable and more consistent with the physical characteristics of the interaction between the aircraft and external flow field. The prediction performance for this problem is significantly higher than that of traditional surrogate models.

2. Problem statement and methodology

2.1 Basic model and parameters definition

Fig. 1 shows the basic model for the ducted propeller studied in this work, including important dimensions, working condition parameters, aerodynamic definitions. Associated dimensionless coefficients of important aerodynamic parameters are defined as

$$C_{Ttot} = \frac{T_{tot}}{\rho \Omega^2 D_{fan}^4} \tag{1}$$

$$C_L = \frac{2L}{\rho V_\infty^2 S} \tag{2}$$

$$C_T = \frac{2T}{\rho V_\infty^2 S} \tag{3}$$

$$C_Q = \frac{Q}{\rho \Omega^2 D_{fan}^5} \tag{4}$$

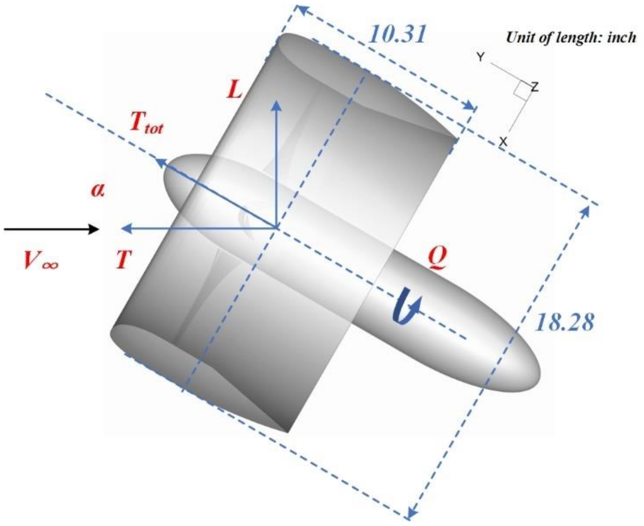

Fig. 1. Basic model and parameters of a ducted propeller.

2.2 Parameterization method

Considering the structure and the clearance between the propeller and the wall, we only control deformation on the leading edge of the duct. A modified shape parameterization method realizes the accurate description of the duct profile, especially for the control of leading edge shape. Hicks-Henne shape function is chosen to represent the airfoil shape by superimposing analytic functions[5]. The shape of the airfoil is defined by the baseline airfoil, shape functions and their coefficients, which can be written as

$$\bar{y}(\bar{x}) = \bar{y}_b(\bar{x}) + \sum_{k=1}^{N} \delta_k f_k(\bar{x}) \tag{5}$$

where $\bar{y}_b(\bar{x})$ is the shape of the baseline airfoil, $\bar{x} = x/c$, N is the number of parameters controlling the shape, δ_k is the coefficient, $f_k(\bar{x})$ is chosen shape function, $\delta_k f_k(\bar{x})$ is the disturbance to the baseline airfoil. 10 modified Hicks-Henne shape functions are used to change 20% of the airfoil, with the following expressions,

$$f(x) = \begin{cases} 0.5(1-\bar{x})^{0.25}(1-5\bar{x})e^{-20\bar{x}}, & k = 1,6 \\ 0.25sin^3\left[\pi(5\bar{x})^{e(k)}\right] \quad , & k \in \{2,3,4,5\} \cup \{7,8,9,10\} \end{cases} \tag{6}$$

$$e(k) = \frac{ln0.5}{ln(x_k)} \tag{7}$$

where $x_k = 5\bar{x}$. When k is taken as {2, 3, 4, 5} or {7, 8, 9, 10}, $\bar{x}$ is taken as {0.04, 0.08, 0.12, 0.16} correspondingly. Ten coefficients from $\delta_1 \sim \delta_5$ and $\delta_6 \sim \delta_{10}$, i.e., shape parameters, are introduced to control the shape of the upper and lower surfaces of the airfoil, respectively. The modified Hicks-Henne shape functions are shown in Fig. 2.

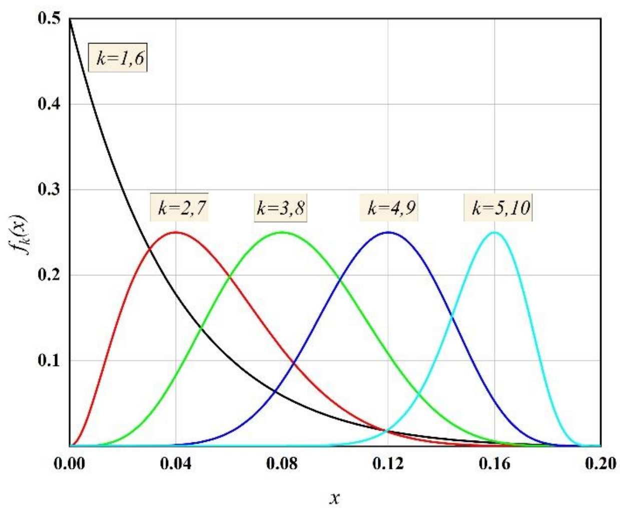

Fig. 2. Modified Hicks-Henne shape functions.

In order to avoid incorrect geometric shapes, combined with the flight state of the ducted propeller vehicle, the variable design space of 10 shape parameters and 2 operating parameters is shown in Table I.

Table I The variable design space with 10 shape parameters and 2 operating parameters.

Shape parameters	**Lower bound**	**Upper bound**	**Shape parameters**	**Lower bound**	**Upper bound**
V_∞	**0**	**30**	α	**0**	**30**
δ_1	**-0.1**	**0.1**	δ_6	**-0.1**	**0.1**
δ_2	**-0.05**	**0.05**	δ_7	**-0.09**	**0.04**
δ_3	**-0.04**	**0.04**	δ_8	**-0.04**	**0.03**
δ_4	**-0.03**	**0.03**	δ_9	**-0.03**	**0.02**
δ_5	**-0.01**	**0.01**	δ_{10}	**-0.01**	**0.01**

2.3 Numerical simulation and validation

A quasi-steady numerical simulation method based on Reynolds Averaged Navier Stokes (RANS) and Multiple Reference Frame (MRF)[6] is used to investigate the aerodynamic performance of ducted propeller. The mesh of the ducted propeller is shown in Fig. 3.

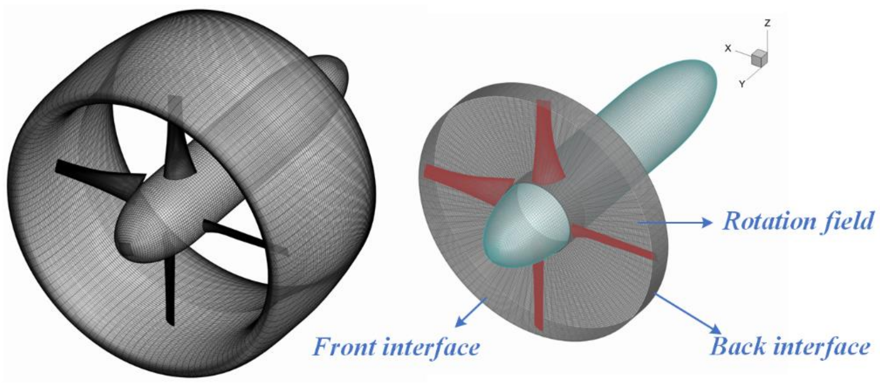

Fig. 3. Grid details of the ducted propeller.

According to the data provided in literature [7], the comparisons of the lift coefficient C_L and forward thrust coefficient C_T with the experimental results are shown in Fig. 4. It can be concluded that the calculation method used in our work has high reliability.

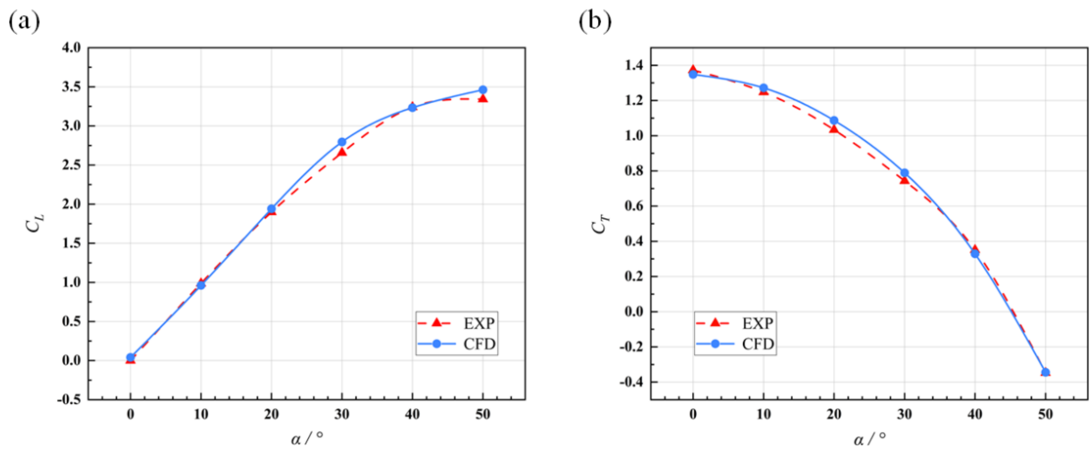

Fig. 4. Comparisons between experiments and CFD in term of (a) lift coefficients C_L (b) forward thrust coefficients C_T.

Optimal Latin Hypercube Design (OLHD)[8] method is used as DOE in our work. 400 sampling points are selected initially in the design space consisting of each parameter in Table I, and construct complete dataset by CFD to train the neural network.

2.4 Structure of network

The surrogate model established in our work is built by the neural network, which can quickly predict the aerodynamic performance of the ducted propeller. We consider the input features as 2 operating parameters V_∞,α, and 10 shape parameters $\delta_1 \sim \delta_{10}$, as shown in Table I, and the output features as 4 aerodynamic performance parameters, C_{Ttot}, C_L, C_T, C_Q, which are defined in equation (1) to (4).

Deep Neural Network (DNN) is a multi-layer unsupervised neural network, which uses the output features of the previous layer as the input of the next layer for learning, and mapping features layer by layer. Considering that the physical properties, magnitude, and design space of the 10 shape parameters and the 2 operating parameters differ greatly, and the aerodynamic performance is sensitive to each parameter, we isolate the input parameters and training them separately to fully explore and extract the features of each data before combining them. An Optimized Neural Network structure combining the High-order component and Low-order component is developed. The High-order component is a DNN that can capture high-order features, accepting the normalized features as input. The core idea of Low-order component is Cross Layer, which could learn feature interactions between parameters with different characteristics. The network structures of DNN and the Optimized network are shown in Fig. 5.

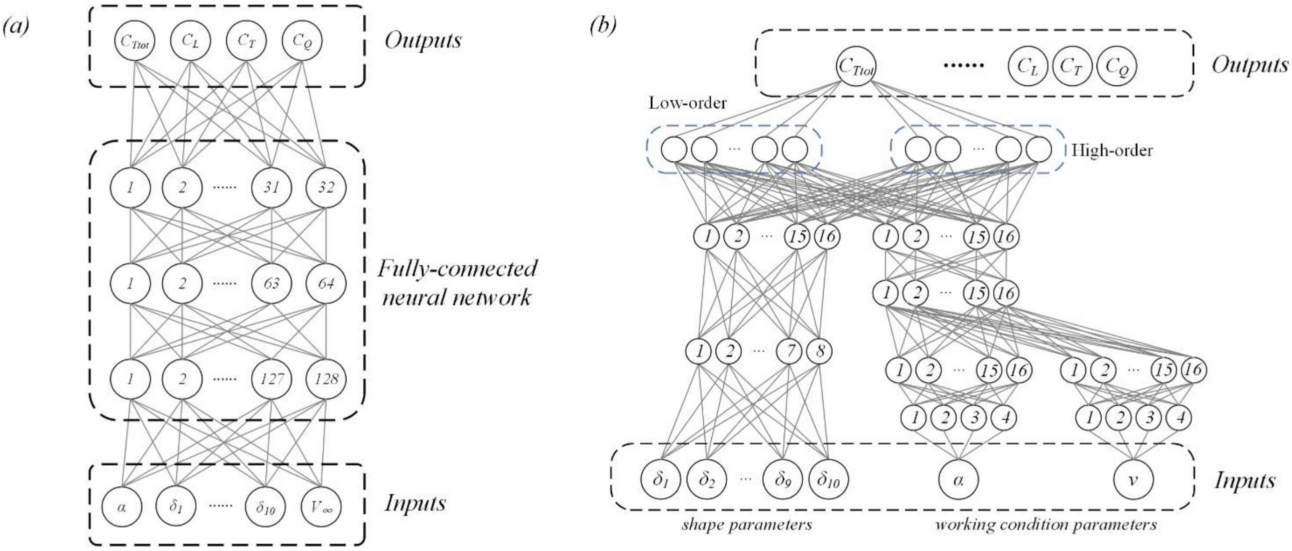

Fig. 5. Structure of (a)DNN and (b)Optimized network

3. Results and discussion

We generated 400 samples with the different combinations of working condition parameters and shape parameters by OLHD, and calculate the aerodynamic data according to the CFD method described above. 90% samples are normalized and processed as the training set, and the remaining 10% samples are used as the validation set. The trained network can predict the aerodynamic performance of a duct propeller for any combination of working condition and shape parameters in the design space. The loss functions in the training processes for 10,000 iteration steps of DNN and Optimized Networks are shown in Fig. 6, and the training is finished with the convergence of loss function.

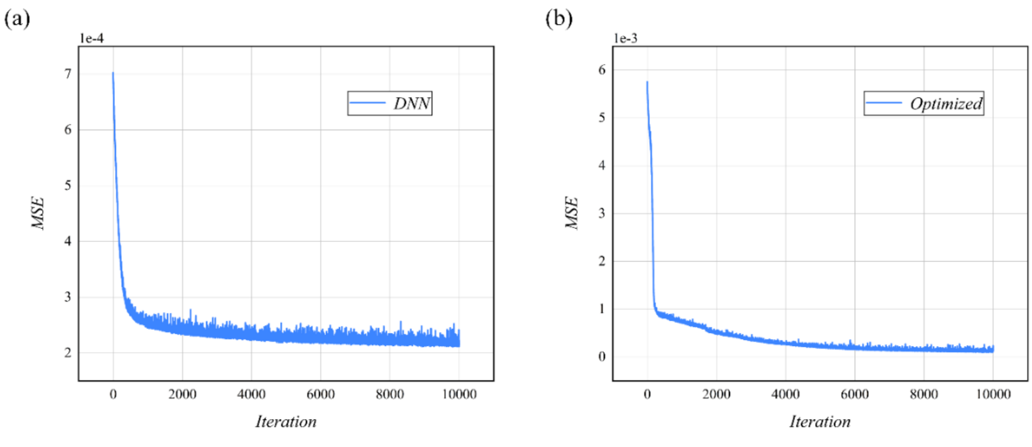

Fig. 6. Loss function curve during training of (a) DNN and (b) the Optimized Network.

We verify the trained neural network surrogates using R^2, as shown in Table II. R^2 can be expressed as

$$R^2 = 1 - \frac{\sum_i \left(y_p^{(i)} - y^{(i)}\right)^2}{\sum_i \left(\bar{y} - y^{(i)}\right)^2} \tag{8}$$

where $y^{(i)}$ is the model observation, $y_p^{(i)}$ is the prediction and $\bar{y}$ is the sample average value. Fig. 7 provides a closer look into the predictions versus model observations on the validation set.

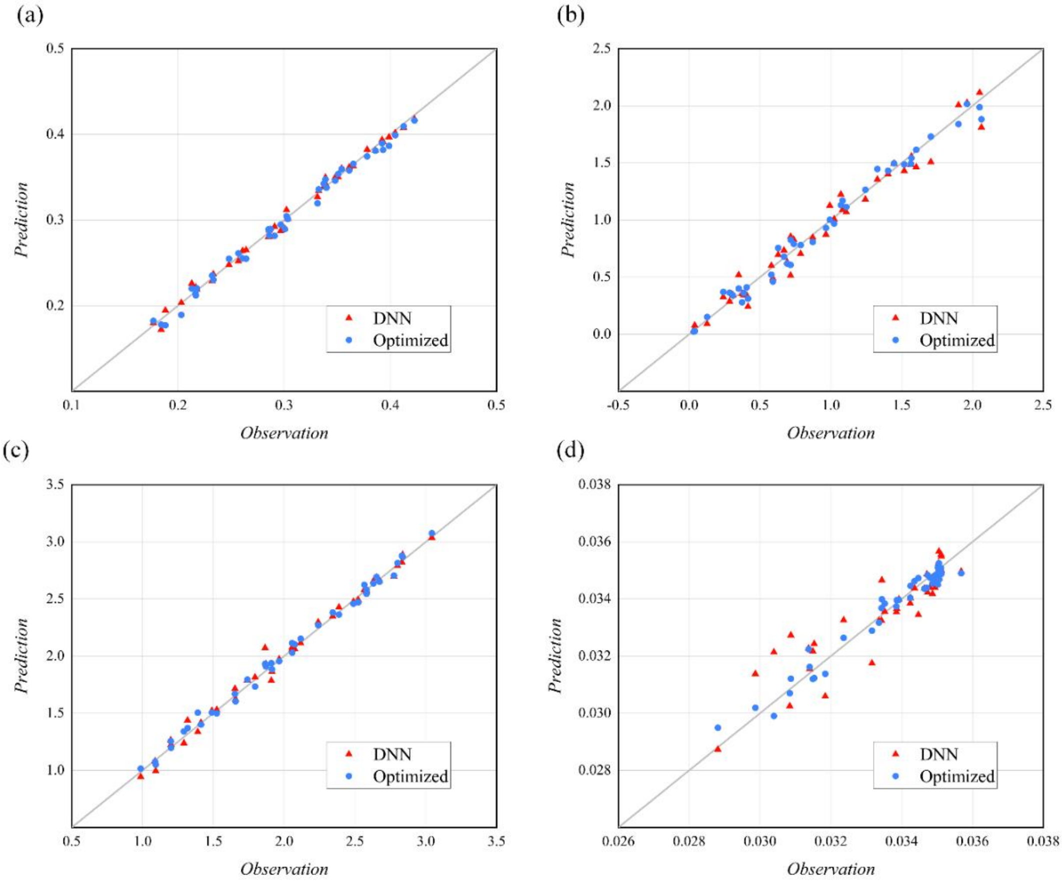

Fig. 7. Comparison of prediction and observation of (a) C_{Ttot} (b) C_L (c) C_T (d) C_Q.

Table II R^2 for the neural network surrogates.

R^2	DNN	Optimized
C_{Ttot}	0.9943	0.9916
C_L	0.9705	0.9845
C_T	0.9904	0.9946
C_Q	0.8226	0.9617

The R^2 values shows that two networks have similar prediction performance and high precision. In more detail, the prediction precision of the Optimized Network is slightly higher than that of DNN, especially when predicting C_Q. Considering that the propeller rotational speed is constant, the values of C_Q are very close when under various working conditions, which is a challenge for the DNN network to predict concentrated values. The Optimized Network has significantly improved the precision of predicted C_Q. In conclusion, the Optimized Network exhibits better prediction performance compared with the DNN.

The computational time of the quasi-steady simulation is about 2000s, while the neural network trained by NVIDIA GeForce GTX 1650 takes sonly 0.06s to obtain the aerodynamic parameters for a specified case. It can be seen that the application of the surrogate model greatly improves the prediction efficiency, which will be conducive to our subsequent analysis. All of the simulations in this work are performed on an Intel(R) Xeon(R) Gold 6238R CPU processor running at 2.20 GHz with 28 cores and 125 GB RAM memory.

We also investigate the generalization capabilities of the established surrogates. We extrapolated the two working condition parameters V_∞ and α by 10% to test whether the surrogate model can make accurate predictions for data not included in the training set. The prediction results with 10% V_∞ and α are shown in Fig. 8(a) and (b). As this figure shows, DNN has the ability to predict data outside the training set better than the Optimized Network. The generalization capabilities can be checked using Average Percent Error (APE) as shown in Table III. For C_{Ttot}, C_L, and C_T, the APE of DNN is all within 3%, while the error of C_Q is less than 10%. is. Most of the errors that Optimized Network predicts are in the 10% range, but in the region of 17%.

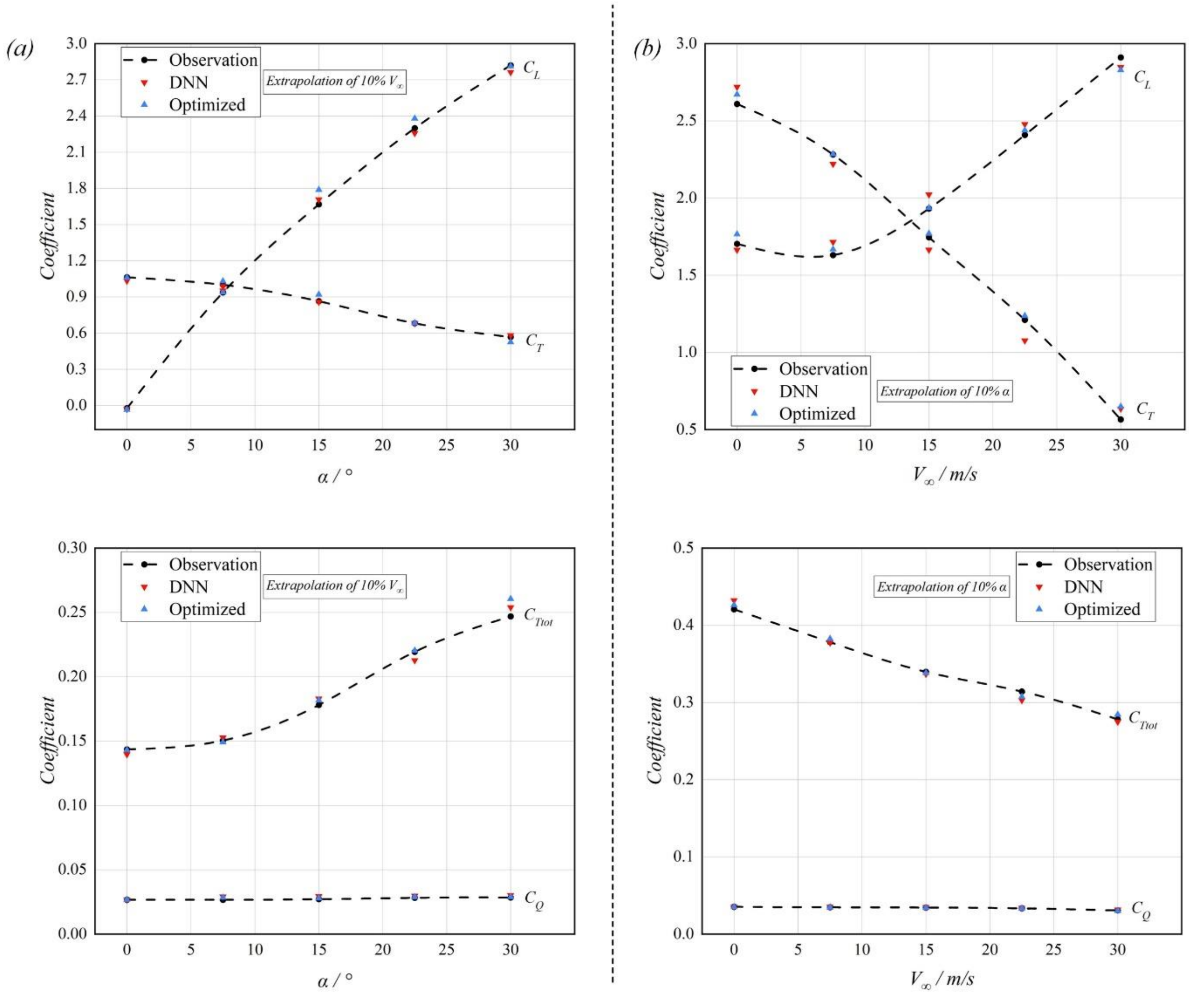

Fig. 8. Prediction using two networks with 10% extrapolation of (a) V_∞ and (b) α respectively.

Table III APE for the neural network surrogates generalization capabilities..

APE(%)	DNN	Optimized
C_{Ttot}	≤2.99	≤8.02

C_L	≤2.41	≤14.05
C_T	≤2.72	≤15.51
C_Q	≤9.35	≤8.38

Response surface model and kriging model are also built based on the Isight platform to evaluate the performance of traditional surrogates and neural network surrogate. The prediction precision of the prediction is checked by different methods using the Mean Absolute Error (MAPE) as shown in Table IV. We can conclude that the prediction accuracy of the neural network surrogate is much higher than the traditional surrogate for all flight features in our study. The structure of the neural network is able to fully integrate the shape of the duct and working condition parameters

Table IV Performance comparison of different surrogate models.

MAPE(%)	Optimized Network	response surface model	kriging model
C_{Ttot}	1.4066	2.3298	4.8709
C_L	7.7888	12.3137	15.7977
C_T	1.4982	3.6011	7.8625
C_Q	0.9079	1.7740	1.1762

To summary, the deep learning based surrogate model exhibits high precision, efficiency and a certain generalization capability. The prediction precision of Optimized Network is slightly higher than that of DNN, but DNN is better at generalization capability. Compared with traditional surrogate models, deep learning-based surrogates can better explore data feature relationships and have higher prediction accuracy and interpretability. In the future deep learning based surrogate models can be applied to a variety of domains.

4. Conclusion

In this work, a deep learning based method for aerodynamic performance prediction of ducted propellers is proposed. The established deep learning based surrogate model can predict the aerodynamic performance within 0.06s under different shapes and working conditions, which greatly reduces calculation consumption. Two neural networks based on optimal network structures, the DNN and the Optimized Network, are used to build surrogate models and compared in this paper. The training results show that the Optimized Network is more advantageous in terms of prediction precision. For this problem, neural network surrogate model is more interpretable and performs better than traditional surrogate models, such as response surface model and Kriging model.

References

[1] Li X, Guo Z, Liu Z, Chen Q. Influence of Ducted Fan Profile Parameters on Aerodynamic Characteristics[J]. Journal of National University of Defense Technology, 2016,38(04):28-33. https://doi.org/10.11887/j.cn.201604005

[2] Han Z H, Xu C Z, Qiao J L. Recent progress of efficient global aerodynamic shape optimization using surrogate-based approach[J]. Acta Aeronautica et Astronautica Sinica, 2020, 41(5): 623344. https://doi.org/10.7527/S1000-6893.2019.23344

[3] Lafronza L, McAlpine A, Keane A J, Astley R J. Response surface method optimization of uniform and axially segmented duct acoustics liners[J]. Journal of Aircraft, 2006, 43(4): 1089-1102. https://doi.org/10.2514/1.17727

[4] Qing J, Hu Y, Wang Y, Astley R J. Kriging assisted integrated rotor-duct optimization for ducted fan in hover[C]//AIAA Scitech 2019 Forum. 2019: 0007. https://doi.org/10.2514/6.2019-0007

[5] Kulfan B, Bussoletti J. "Fundamental" Parameteric Geometry Representations for Aircraft Component Shapes[C]. In 11th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference. American Institute of Aeronautics and Astronautics, 2006. https://doi.org/10.2514/6.2006-6948

[6] Issa R, Luo J Y, Gosman D. Prediction of Impeller Induced Flows in Mixing Vessels using Multiple Frames of Reference[C]// 4th European Conf. on Mixing, IMechE Symposium Series No 136. 1994.

[7] Goodson K W, Grunwald K J. Aerodynamic loads on an isolated shrouded-propeller configuration for angles of attack from-10 deg to 110 deg[R]. 1962.

[8] Celik I B, Ghia U, Roache P J, Freita C J, Coleman H, Raad P E. Procedure for estimation and reporting of uncertainty due to discretization in CFD applications[J]. Journal of fluids Engineering-Transactions of the ASME, 2008, 130(7). https://doi.org/10.1115/1.2960953

Acknowledgements

This work was supported by the National Natural Science Foundation of China (NO. U2241274)，the Rotor Aerodynamics Key Laboratory Foundation of China Aerodynamics Research and Development Center (No. RAL202302-2) and the specialized research projects of Huanjiang Laboratory

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