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Куихада Пиокуинто Х.П.

DESIGN OF A MULTI-LAYER PERCEPTRON FOR STEADY NONLINEAR AERODYNAMIC RESPONSE PREDICTIONS

In recent years, deep learning algorithms have been widely used in the field of aerodynamics, either as prediction models or reconstruction of flow fields. In the field of aerodynamic response prediction for stationary flows, Multilayer Perceptrons (MLP) and Convolutional Neural Networks (CNN) have been the architectures of greatest interest. Although CNN architectures have demonstrated better performance than MLP, they have been used for reverse design processes with great success. This paper presents an MPL architecture that was trained with profile geometries modeled with Bezier-PARSEC parameters of existing profiles. The results obtained were relatively good, using a database of 800 elements, regression analyses demonstrated good predictions of lift, momentum and drag coefficients, using a single network to predict the three coefficients.

Keywords: multi-layer perceptron, parameterization Bezier-PARSEC, KERAS TENSOR FLOW.

INTRODUCTION

Models based on Artificial Intelligence techniques that, being based on highly reliable data from physical systems, have achieved good reliability in aerodynamic applications. These surrogate models have the added advantage (efficiently and accurately of predicting solutions to nonlinear problems [1].

Neural networks aimed at modeling aerodynamic data have the following approaches: aerodynamic response prediction and reconstruction of flow fields. Aerodynamic response predictions refer to the utilization of appropriate methods to build aerodynamic data models that can express the variation in aerodynamic response parameters (forces or moment coefficients) with the design parameters, and finally output the predicted value of response parameters in the case of given design parameters. Studies in this field start from two aspects: those based on the flow state and those based on both aerodynamic shapes and the flow state.

In steady aerodynamic response predictions, both Multi-layer Perceptron (MLP) Neural Networks and Convolutional Neural Networks (CNN) are feasible [2]. Yilmaz and German [3] believes that the approaches based on CNNs are better than those based on MLPs. Depending on the task the MLP and CNN architectures are feasible, but the key factor affecting the prediction accuracy is the high reliability of the original data in the training set. MLP-based models need to explore new structures to improve the accuracy of prediction. This process is called model-oriented research. CNNs-based models should focus on how to merge the flow state and aerodynamic shapes. This process is called data integration-oriented research [2].

On the other hand, MPLs architectures have been sufficiently precise to be used in airfoil inverse design processes using shape optimization algorithms. Some of these architectures are designed to predict one aerodynamic characteristic at a time. In 1994, Huang et. al. demonstrated that MLPs architectures working in conjunction with Euler method can predict the lift coefficient of a profile with Root Mean Square (RMS) error of 0,67% [4]. To improve the prediction response of MLPs and improve their functionality in reverse design processes, proposals have emerged such as the use of metaheuristic optimization algorithms and improved profile parameterization techniques [5]. In more recent research, in order to achieve better accuracy in the MPLs, the works have focused on the variation of the hyper parameters (number of neurons, number of hidden layers, activation functions, type of optimizer, etc.) of the neural network [1], [6], [7]. Following these lines of research, the methodology developed by Moin et. al. is applied in this work to determine the architecture of an MLP [1].

METHODOLOGY

It was proposed to create a database based on the database of the University of Illinois at Urbana-Champaign [8], which has more than 1600 airfoils. 800 asymmetric airfoils were extracted from this database. In this test asymmetric profiles were used which were modeled with Bezier-PARSEC (BP) parameters (10 parameters describing the bending and thickness curves of the airfoil) and the evolutionary algorithm SHADE E-PSR [9], [10]. Each airfoil was analyzed in Open FOAM to obtain aerodynamic coefficients (C_L - lift coefficient; C_D - drag coefficient, C_M – moment coefficient), the simulation was performed taking into account the Reynolds number equal to 3000000, and using the k-omega SST turbulence model. Aerodynamic coefficients were obtained only at an angle of attack of 0 degrees. A data mining technique of clustering Self-Organizing Maps (SOM) was applied to visualize the grouping and diversity of individuals in the database; it is possible to do a parameter correlation analysis, to determine if any of the BP parameters are unnecessary [11].

All the evaluated neural networks were programmed with Python using the Tensor Flow - Keras libraries. The Mean Square Error (MSE) was maintained as the loss function, while the Root Mean Square Error (RMSE) and the R^2 values were maintained as metrics to measure the performance of neural networks. The Rectified Linear Unit (ReLU) was used as the activation function in all layers. Each network was trained for 200 epochs. 90% of the data were used for training, 5% for validation and 5% for testing. All networks will have 10 input parameters and 3 output parameters. The number of hidden layers, the number of neurons per layer and the activation function in the output layer were the hyperparameters evaluated. Like Moin et. al., it started by evaluating the number of layers, and then the number of neurons per layer [1]. In the first three cases, the performance of the architectures was evaluated based on the number of hidden layers (see Table 1). Based on the best architecture, the number of neurons in the hidden layers is now modified (see Table 2).

Table 1. Network performance due to changes in hidden layers

Case	Architecture	R^2			RMSE		
		C_M	C_X	C_Y	C_M	C_X	C_Y
1	10-64-32-3	0,9511	0,8010	0,9770	0,0077	0,0095	0,0263
2	10-64-32-16-3	0,9633	0,7928	0,9798	0,0070	0,0109	0,0244
3	10-64-32-16-8-3	0,9501	0,7213	0,9695	0,0085	0,0110	0,0287

Table 2. Neural network performance due to changes in neurons

Case	Architecture	R^2			RMSE		
		C_M	C_X	C_Y	C_M	C_X	C_Y
2	10-64-32-16-3	0,9633	0,7928	0,9798	0,0070	0,0109	0,0244
4	10-128-64-32-3	0,9604	0,8371	0,9737	0,0074	0,0125	0,0263
5	10-256-128-64-3	0,9649	0,9178	0,9800	0,0073	0,0068	0,0247
6	10-512-256-128-	0,9715	0,9039	0,9770	0,0066	0,0066	0,0250

CONCLUSION

It was possible to verify that the proposed methodology for the determination of the hyperparameters of the neural network was correct for the database developed with the Bézier-PARSEC parameters. Unlike Moin, in this work, the analysis could not be performed by changing the size of the database. Despite the small size of the database, a multilayer perceptron with a prediction of a regular aerodynamic response can be created. The R2 values for the three aerodynamic coefficients still need to be improved, currently a neural network intended for the prediction of aerodynamic coefficients must have R2 values equal to or greater than 0.99. The main idea of improving neural network predictions is to increase the number of profiles in the database. The advantage of having a self-organizing map of the current database is that you know what types of profiles are needed to expand the database and maintain data diversity.

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Ивченко А.В.

СТРУКТУРА И СВОЙСТВА ТЕЧЕНИЙ, ФОРМИРУЕМЫХ В ОКРЕСТНОСТИ ЦИЛИНДРИЧЕСКИХ ТЕЛ ПРИ ВОЗБУЖДЕНИИ ПОВЕРХНОСТНЫХ РАЗРЯДОВ НА ОБРАЗУЮЩЕЙ

Известно [1, 2], что эффективное воздействие на пограничный слой при обтекании тел открывает новые возможности управления не только динамикой полета летательных аппаратов, но и работой их двигателей. Одним из способов воздействия на пограничный слой является возбуждения в нем плазмы поверхност-