Solving Aerodynamics and Aeroelastic Stability Problems through Data

(Bibliography report)

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***Abstract*—The calculation of the aerodynamic coefficients of an airfoil with established methods is a time consuming and computationally expensive process. This work takes a data-driven approach to determine the aerodynamic coefficients of a given airfoil much faster. It uses an already existing data base and tries three different platforms (Keras and SMT in python and Monolith AI) to predict the coefficients as good as possible. The newly obtained surrogate model can then be used to improve the surrogate model of a previous work that delt with aeroelastic instabilities of airfoils which built a surrogate model with a significantly smaller database.**

I. Context

The selection of the airfoil geometry can be seen as one of the most crucial parts in the aircraft design process. It influences the cruise speed, take-off and landing distances and overall determines the aerodynamic performance of the aircraft [11]. In the beginning of the aircraft history the aerodynamic parameters were estimated using wind tunnels. With the rise of available computational power, simulation methods were used for their calculation. Despite the accuracy of these calculations there are also disadvantages. They cost a lot of time and computational power [9].

To reduce the time and needed computational power a deep learning approach will be taken in this work using a database of ten-thousands of airfoils. In deep learning computational networks are built which try to imitate the working processes in the human brain. Inputs are fed into the network which consists of numerous layers of so-called neurones. They process the data and issue an output. This output is then compared to the output that should have been issued. Because of the difference from the predicted value and the true value the network can learn. After the learning phase it can predict outputs from not-learned input values. [12]

In a previous work an aeroelastic problem was to be solved using a deep learning approach. The aim was to morph an airfoil whose centre of gravity was suddenly changed during an aeroelastic simulation which led to an instability. The neural network should find an airfoil that gets back into a stable manner. BEZIER-Parsec 3434 parameters were used to describe 1000 airfoils of the 4th NACA family in the database. Using XFoil the aerodynamic coefficients and the centre of gravity of the airfoil were determined. With this database a neural network with a feed-forward architecture with three hidden layers was trained. For the aeroelastic model a structural module and an aerodynamic module were built and combined to the aerolelastic model. Finally, the aeroelastic code and the neural network were coupled, and results could be obtained. [5]

Because of the small database and its easy architecture, the obtained surrogate model is not as powerful. To improve the model a different database [2] will be used . To build the database the researchers first performed a singular value decomposition of the camber and thickness lines of 1172 airfoils in the UIUC database to obtain their mode shapes. Then a big database for the subsonic and transonic regimes was built with 81000 and 32400 airfoils respectively that were controlled by 14 and eight mode shapes, respectively. A reconstructed airfoil in the subsonic flow regime can be seen in Fig. 1. [10]

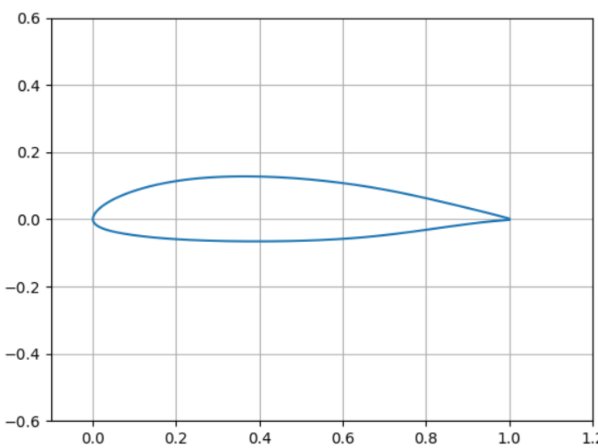

Fig. 1. A random airfoil in the subsonic regime generated out of the mode shapes.

It followed a construction of a surrogate model to predict the aerodynamic coefficients of the airfoils. A gradient enhanced kriging with partial least squares (GE-KPLS) with a mixture of expert approach was taken. A GE-KPLS is a development of a gradient enhanced kriging (GEK) model. A GEK can reduce the number of evaluations drastically by using the gradient information but two problems occur with the rise of sample points and independent variables. Firstly the correlation matrix grows rapidly and secondly more hyperparameters have to be estimated. GE-KPLS solves this problem by using the least squares method [4]. A mixture of experts was introduced because the amount of data is still difficult to handle for the GE-KPLS. Two independent surrogate models were built for the subsonic and transonic regimes, respectively.

In the following work the GE-KPLS was improved to a variation of an artificial neural network. The applied neural network uses the Sobolev training method. There the gradient information is passed into the loss function of the training samples during the training phase in addition to the target values [6]. Bouhlel et al. [1] modified the Sobolev training method for their artificial neural network slightly, so the gradient information is passed gradually into the loss function. Their obtained results show an improvement to the first approach with the GE-KPLS network and one surrogate model could be used for both regimes.

Using two different python packages, Keras and SMT, and the platform Monolith AI the learning of the database used in the previously discussed papers will be learnt. Keras is a deep Learning application programming interface which uses the platform tensorflow, a well-established platform for deep learning problems [7]. Keras provides an easy user interface with high flexibility. SMT is a newly developed artificial intelligence platform which provides a collection of neural network modelling methods and sampling and benchmark functions. It focusses on the use of derivatives which can be used for gradient enhanced networks [3]. Monolith AI is an online platform which learns from data of previous calculations that are uploaded to the platform. After the learning of the data the platform can product results for new structures in parameterizing them and also solve optimization problems [8].

II. Problem Statement

Despite having a big database a few problems can occur:

- The hyperparameters for the neural network should be chosen wisely to obtain a network with high accuracy in the training but also in the validation and test phase.
- For the aeroelastic problem the centre of gravity is needed which is not yet included in the database used in this work.
- Coupling the surrogate model with the aeroelastic code can be difficult.

III. First Results and Future Work

First work was to visualize the data in the database and perform a first very simple application of a neural network. The work will be focussed on the subsonic regime. It was possible to get the shape of an airfoil in using the mode shapes from the singular value decomposition and the mode shapes from the picked airfoil as seen in Fig. 1. Right now, the database consists of three different data bases for each aerodynamic coefficient. A first very simple network was built with the Keras package. It just consists of the input layer, one hidden layer with 1000 neurones and the output layer. The activation function is the ReLu function, and the Adams optimizer is the used optimizer. As the loss function the mean absolute error was chosen. Chosen metrics were the R2 and RMSE value. No specific sampling methods were chosen. As an example, the results from the network learning the data for the drag coefficient is shown in Fig. 2. It is observable that for the very simple architecture the network can learn the data reasonably well after 100 epochs despite having some outliers. But one must keep in mind that it is just one output it must predict. The aim is to make a network that predicts all three aerodynamic coefficients.

For future work, the database will be learnt by all three presented platforms. For SMT and Keras the architectures of the networks will get gradually more complicated and different approaches will be taken to obtain better results. After that, a comparison between the three platforms will be made. Finally, the new network could be applied on the aeroelasticity problem to improve its database and performance.

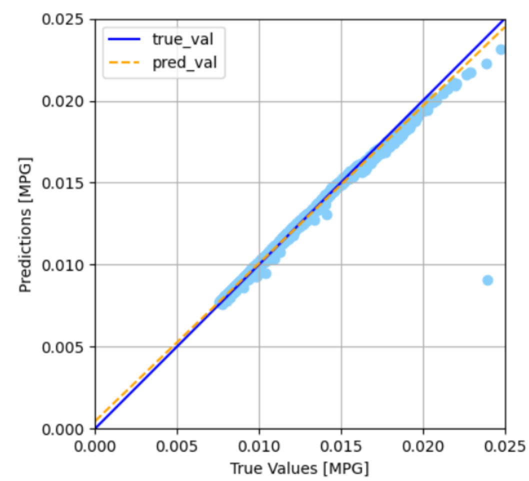

Fig. 2. First results with the one hidden layer network for the prediciton of the drag coefficient. The points represent the predicted values

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