Generating near-optimal meshes using green AI

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ABSTRACT

When optimising a design, multiple simulations for different operating conditions and geometric configurations are required. The process of generating the most appropriate mesh for each operating condition and geometric configuration is usually too time consuming in an industrial environment. This is mainly due to the excessive human intervention and expertise that is required at this stage to generate meshes capable of capturing all relevant features of the solution with the minimum number of elements possible.

In many occasions, it is preferred to generate an excessively refined mesh that is capable of capturing all the solution features for all operating conditions and geometric configurations. This obviously leads to larger CPU times and carbon emissions when running the solver, but completely removes the burden of mesh generation. As an example, Figure 1 shows an unstructured tetrahedral mesh of 40 million elements around a wing. The mesh is designed to capture all the solution features when varying the angle of attack and the free stream Mach number.

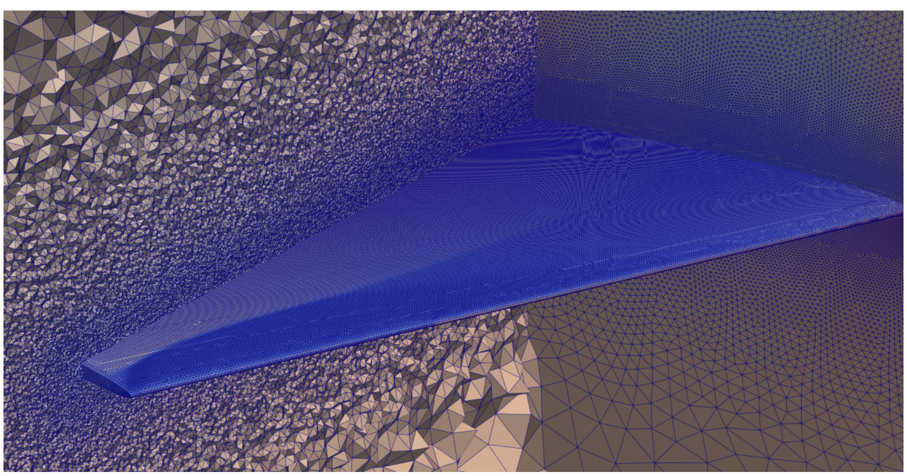
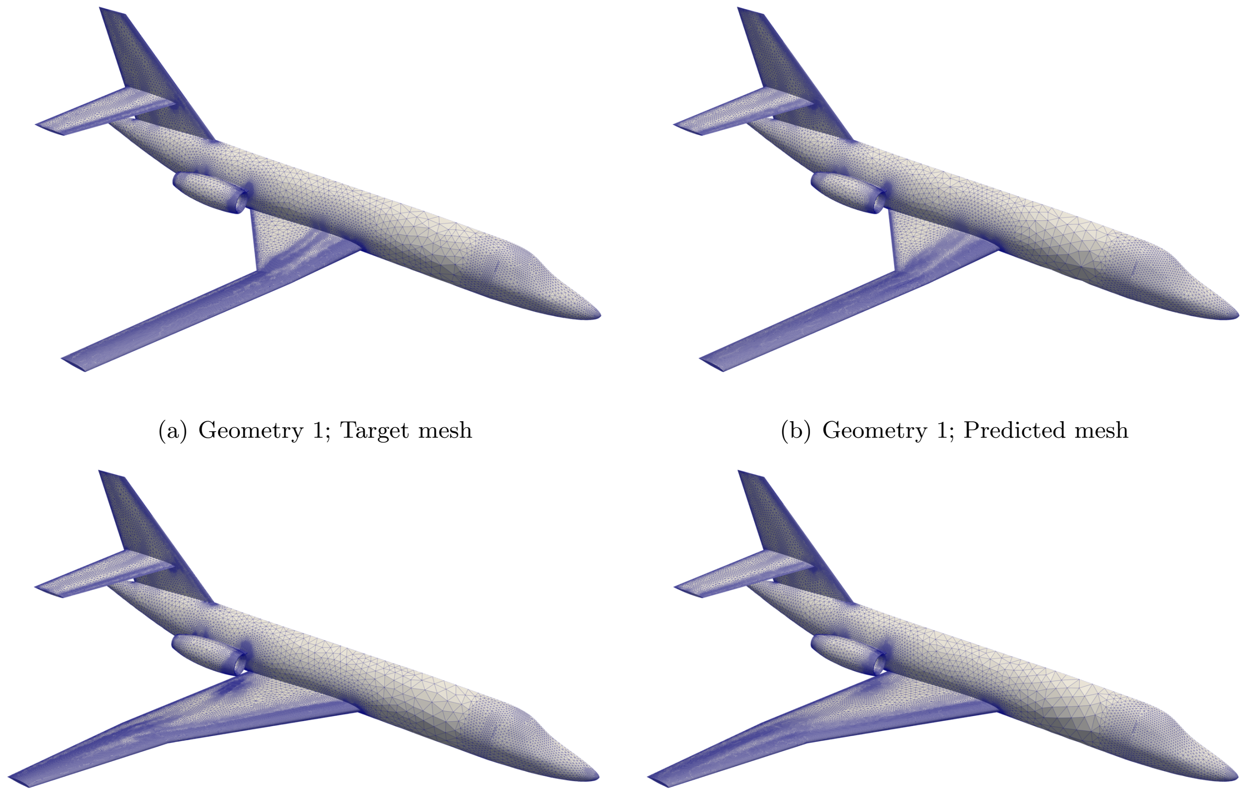


Figure 1: Mesh to simulate the flow around a wing for various flow conditions.

In this talk, two strategies to predict the near-optimal spacing for a given operating condition and geometric configuration will be presented. The first strategy aims at predicting the position and spacing characteristics of a set of point sources that will be used in the on-line phase to produce a near-optimal mesh [1]. The second strategy aims at predicting the a discrete spacing in a given background mesh, which again is then used in the on-line phase to produce a near-optimal mesh [2]. Both approaches will enable utilising the vast amount of data that would exist in industry to predict the spacing that is required to produce near-optimal meshes.

The two strategies will be applied in the context of three-dimensional compressible flow simulations involving full aircraft configurations. As an example, Figure 2 shows the target mesh and the predicted mesh for two different geometric configurations corresponding to cases not seen by the artificial intelligence (AI) system during training. The flow conditions correspond to an angle of attack of 2° and a free-stream Mach number of 0.78. The variation of the geometric parameters induce a significant variation of the flow features and the predicted spacing is in excellent agreement with the target spacing. It is worth noting that less than 60 cases were considered to train the AI system capable of predicting the spacing, and in this example the problem involves 11 geometric parameters.



(a) Geometry 1; Target mesh

(b) Geometry 1; Predicted mesh

(c) Geometry 2; Target mesh

(d) Geometry 2; Predicted mesh

Figure 2: Target spacing (left) and predicted spacing (right) for two different geometric configurations.

The two approaches will be analysed and compared in terms of the AI architecture, the number of training cases required, the accuracy in the predicted spacing and the accuracy in the subsequent flow simulations. In addition, the benefits of using the predicted meshes, instead of using over-refined meshes, as shown in Figure 1, will be discussed, both in terms of efficiency and carbon emissions. The examples will also include the latest efforts in predicting not only isotropic spacing functions but also anisotropic spacing functions.

REFERENCES

[1] C. Lock, O. Hassan, R. Sevilla, and J. W. Jones. Meshing using neural networks for improving the efficiency of computer modelling. To appear in *Engineering with Computers*, DOI 10.1007/s00366-023-01812-z.

[2] C. Lock, O. Hassan, R. Sevilla, and J. W. Jones. Predicting the near-optimal mesh spacing for a simulation using machine learning. *SIAM International Meshing Roundtable*, 2023.