CFD PARAMETER CALIBRATION BASED ON DEEP LEARNING

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Key words: CFD, Finite element solvers, Turbulence, Heat Transfer, Deep Learning, Parameter Calibration.

1 AEROTHERMAL MODELING AND IMPLICIT LARGE SCALE SIMULATIONS

Jet impingement cooling is one of the most frequently used techniques for turbine blade cooling. Since the vortex structure and the heat transfer distribution in impingement cooling are extremely complex, the study on this case will not only help people improve the cooling method of turbine blades, but also further discover the law of turbulent flow under extreme conditions.

The present work aims at characterizing the flow field and heat transfer for a schematic but realistic vane cooling scheme, as shown in Figure 1.1. The turbine vane is composed by 15 holes on the intrados (lower part), 15 holes on the extrados (upper part) and 9 holes on the semi-cylinder part. In the literature, detailed experimental database of the investigated configuration can be found for both velocity and heat transfer measurements in [1, 2].

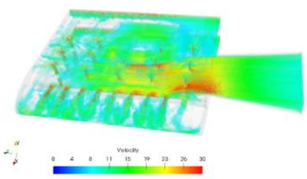


Figure 1.1 Simulation case of the 39 holes

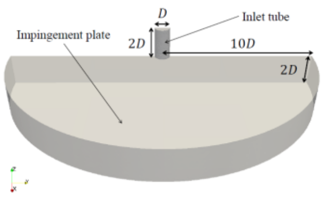


Figure 1.2 Simulation case of the single jet impingement cooling[4]

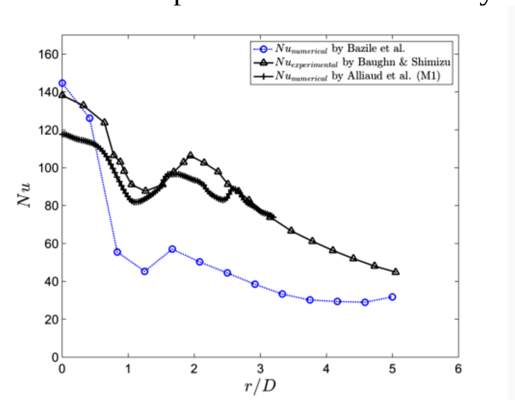
For this 39 holes simulation case, the most refined simulation mesh used 25M elements on 1K cores to predict the flow structure. Since the flow is extremely complex, this mesh is still not refined enough that it still exists some non-negligible deviations from experimental results. The mesh resolution is expected no less than 2 billion elements for several thousand timesteps in order to capture different scales of the coupled aerothermal flows. Moreover, the complexity of the physical parameter analysis that we shall investigate in this paper, let us consider this study on a single jet impingement cooling, a well-documented test case of the literature [3].

2 SINGLE JET IMPINGEMENT COOLING MODEL AND CALIBRATION

The single jet impingement cooling test case consists in a single unconfined round jet that hits normally a flat plate at a certain Reynolds number. The Reynolds number is defined by the impingement pipe diameter and the bulk velocity.

This flow configuration is known to lead a secondary peak in the Nusselt number distribution, as shown in Figure 2.1, when Reynolds number Re=23K and nozzle to plate distance of H/D=2 [3]. Since the near-wall complex flow structure is difficult to capture, the secondary Nusselt peak and the near-wall velocity profiles are consequently hard to predict accurately. The coupling between Flow (Navier Stokes) equations and heat transfer equation used in LES model is performed thanks to the Smagorinsky model that affects the viscosity, and the Prandtl number that impacts the conductivity [7].

Comparing the experimental radial velocity profiles with numerical results calculated by LES model, it can be seen that the velocity profile doesn't match the experimental results, as shown in Figure 2.2 [4]. This discrepancy could be a result of several factors: boundary layer resolution, boundary conditions and also the coupling models. In this paper we assume that the two issues are resolved and we focus only on the coupling models. Indeed, inaccurate volume mass flow implies inaccurate viscosity.



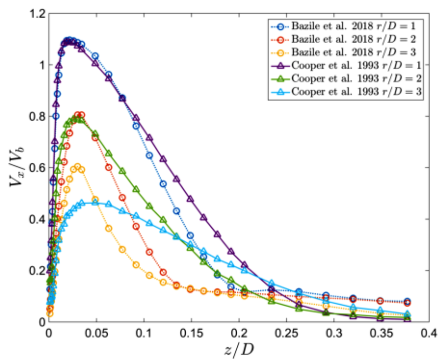


Figure 2.1 Figure 2.2

Figure 2.1 Comparison of radial Nusselt number distribution with an experimental reference from A.Bazile et al. in [4] and from Baughn et al. in [5] and with a numerical reference from Aillaud et al. in [6].

Figure 2.2 – Radial velocity profiles in the boundary layer at r/D = 1, 2, & 3

Since the relationship between these two parameters and the other parameters in calculation is unknown, we plan to build two functions depends on radius to calibrate these two parameters first. Then the relationship between these parameters could be calculated after having an accurate Smagorinsky constant distribution and Prandtl number distribution.

In this simulation, the calculation case is based on the case did by A.Bazile [4]. It can be seen that in some distribution setting of Smagorinsky constant and Prandtl number, the velocity profile at r/D = 3 is closer to the experimental results as shown in Figure 2.3, and the Nusselt number arise to the same level as experimental results at the region of r/D > 2.5 as shown in Figure 2.3. These observations indicate that it is possible to calibrate the Nusselt number and velocity profile of the impingement cooling case by adjusting the Smagorinsky constant and the Prandtl number.

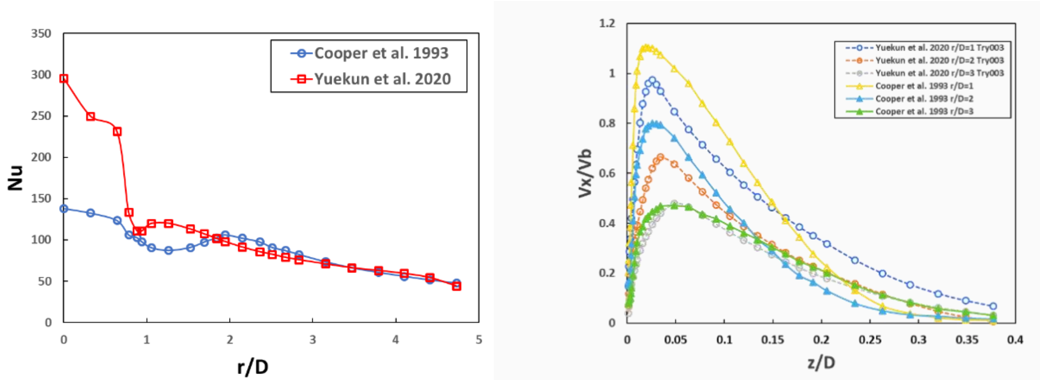


Figure 2.3 Comparison the deep learning prediction Nusselt number distribution (left) and near-wall velocity profile on r/D =1.0, 2.0 and 3.0 (right) with new Smagorinsky constant and Prandtl number

According to functions (2.1) to (2.3), both the Smagorinsky constant and the Prandtl number influence the velocity and the Nusselt number at the same time. Thus, the calibration of these two parameters is a non-linear process, and can hardly be completed manually. In this condition, using deep learning to calibrate these two parameters is one of the most probable method to obtain an accurate Smagorinsky constant distribution and Prandtl number distribution.

$$\nu_{total} = \nu_{fluid} + \nu_{temperature} + \nu_{eddy} \tag{2.1}$$

$$\nu_{eddy} = \left(C_S \Delta g\right)^2 \sqrt{2\bar{S}_{ij}\bar{S}_{ji}} \tag{2.2}$$

$$\lambda_{total} = \frac{\nu_{total}\rho C_P}{\mathrm{Pr}} \tag{2.3}$$

3 CALIBRATION MODEL BASED ON DEEP LEARNING

In the calibration process, there is a loop including parameter input, calculation result acquisition and parameter adjustment. Since the computational cost in CFD, especially in coupled LES and heat transfer model, is extremely expensive, the use of deep learning to predict the CFD results and to simplify the result acquisition process becomes one of the most important links in the calibration process.

For the calibration process, we assume that the numerical models (including LES and heat transfer models) are basically accurate, and the inaccuracy of the Smagorinsky constant and the Prandtl number are the leading factor that causes the calculation inaccuracy.

The calibration with deep learning includes two steps. The first step is using the current CFD simulations to train a low-cost prediction model by using deep learning. The second step consists in the use of the new prediction model instead of the CFD solvers, and executes the calibration loop, until we get an accurate result.

On the first step, the Nusselt number distribution and the velocity profile are considered as labels, and the Smagorinsky constant and the Prandtl number distribution are considered as features. We build a multi-layer artificial neural network which includes two hidden layers to train the prediction model. In the training stage, the LES model results are used to train the program to predict the Nusselt number distribution and velocity profile. The neural network weights are fitted following the CFD solutions for a given Smagorinsky constant and Prandtl number.

On the second step, we use the Stochastic gradient descent method to optimize the calibration loop and to adjust the Smagorinsky constant and the Prandtl number. According to the experiment did by D. Cooper et al. [3], their experimental results provide the near-wall radius velocity profile on six check position (r/D = 0.5, 1.0, 1.5, 2.0, 2.5, 3.0) and the Nusselt number distribution, which include 233 check points. During this process, function (3.1) is considered to be a loss function which defines the accuracy of the calibration.

$$\underset{\left(C_{Si} \quad \Pr_j\right)_{i,j}}{\arg\min}\left(Ave\left(\left|Nu_C - Nu_E\right|\right)\cdot Var\left(Nu_C - Nu_E\right)\cdot \prod_{k=1}^{6}\left(Ave\left(\left|V_{Ck} - V_{Ek}\right|\right)\cdot Var\left(V_{Ck} - V_{Ek}\right)\right)\right) \tag{3.1}$$

$$Ave\left(\left|V_{Cki} - V_{Eki}\right|\right) = \frac{\sum_{i=1}^{n}\left|V_{Cki} - V_{Eki}\right|}{n} \tag{3.2}$$

$$Var\left(V_{Ck} - V_{Ek}\right) = \frac{1}{n}\sum_{i=1}^{n}\left(\left(V_{Cki} - V_{Eki}\right) - \sum_{j=1}^{n} p_j \cdot \left(V_{Ckj} - V_{Ekj}\right)\right)^2 \tag{3.3}$$

After 17 training epochs, for certain input, it can be seen that the prediction results are close to the CFD results, as shown in Figure 3.1. We believe that with more training, the deep learning results will be more accurate and smoother than the current one.

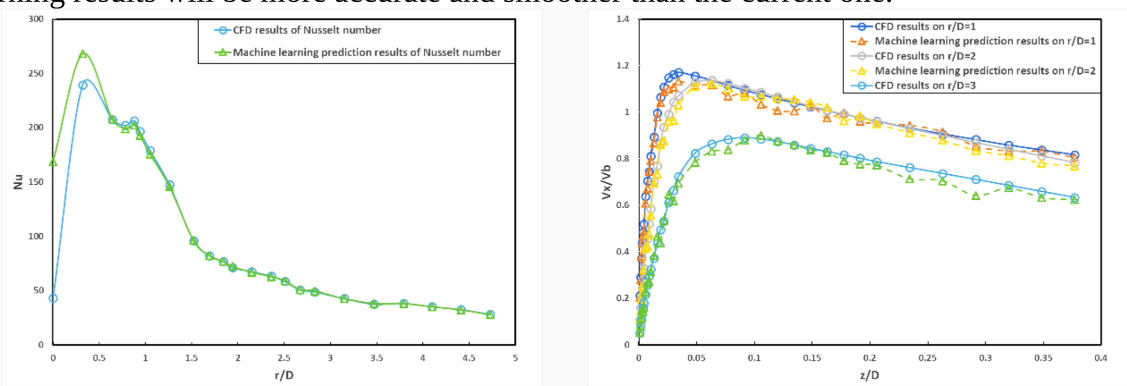


Figure 3.1 Comparison the deep learning prediction Nusselt number distribution (left) and near-wall velocity profile on r/D =1.0, 2.0 and 3.0 (right) with CFD results

4 CONCLUSION

Impingement jet cooling is of paramount interest for aerospace industry. The study of such a problem is very challenging and the associated physics is misunderstood. In this paper, we propose a new calibration model based on a deep learning approach. The two-step deep learning strategy allows to get very promising results through the small numerical data base that we built. We are enriching the data base and improving the deep learning predictor to improve the whole approach. Once we finished the calibration of the single jet impingement cooling case, we will come back to validate the realistic 39 holes test case with accurate calibrated CFD parameters.

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