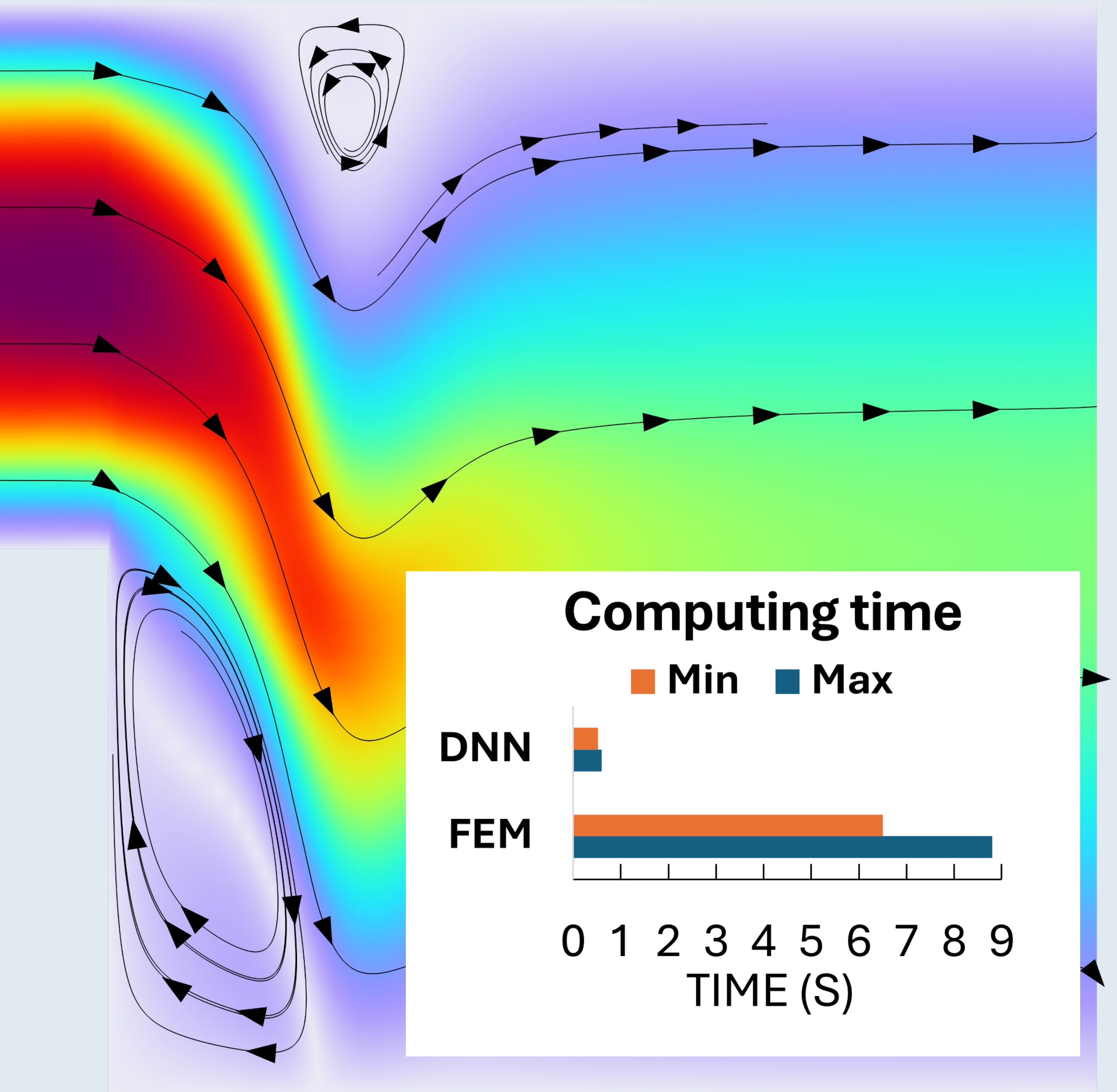

Neural Networks on Backward-Facing Step Flows

Using deep neural networks (DNNs) as an alternative model for simulations in Computational Fluid Dynamics.

M. Rabenanahary
R&D and Simulation, PROTOSTEP, Cergy-Pontoise, France.

Introduction & Goals

Over the last decades, deep learning has increasingly entered physics in search of numerical techniques improvement.

In 2023, COMSOL® introduced ‘Surrogate Models’, including the ability to train non-informed neural networks using experimental data or simulation models generated within the software.

We evaluated the accuracy and time performance of these networks in predicting the backward-facing step steady-state flow for Reynolds numbers (Re) up to ~900.

Such a flow widely occurs around buildings, in aerodynamics, heat transfer, engines, or vehicles (e.g. for air-filter performances, cf. Ref. 1), and has been thoroughly studied in experiments and numerical simulations (e.g., Ref. 2 and 3).

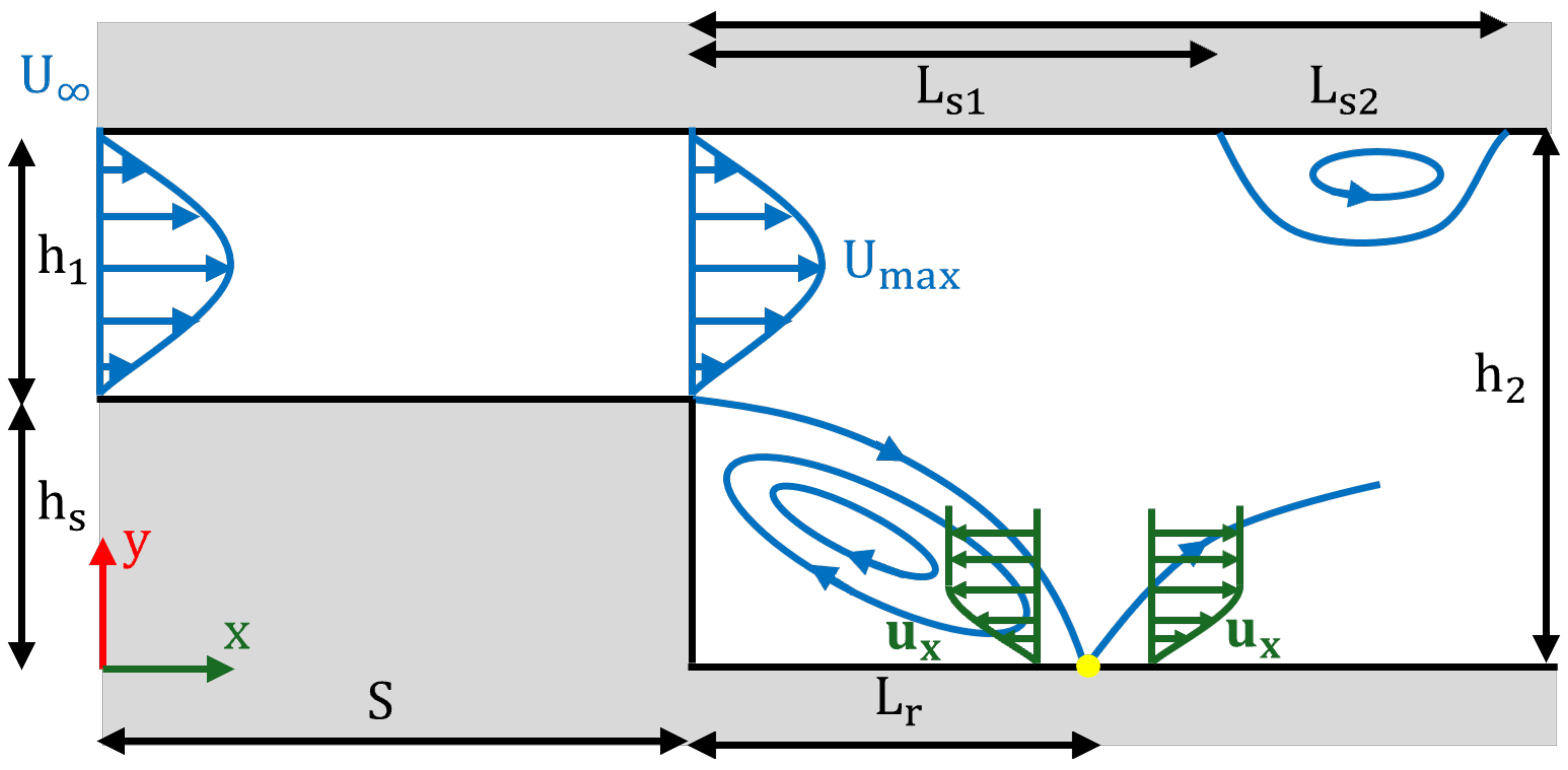

FIGURE 1. Sketch of the backward-facing step (BFS) flow field, and of the velocity profiles around reattachment zone.

Methodology

A fully developed flow goes at various Reynolds numbers $Re < 400$ or 580 through an abruptly expanding channel. 2D incompressible steady-state Navier-Stokes equations are solved:

$$\nabla \cdot \mathbf{u} = 0, \quad \rho(\mathbf{u} \cdot \nabla)\mathbf{u} = -\nabla p + \mu \nabla^2 \mathbf{u}$$

Increasingly tuned DNNs are thus trained with up to ~2.3×10^6 data points. The networks’ accuracies (up to $Re \sim 900$) against experimental data are measured from the lengths of the recirculation regions (L_r, L_{s1}, L_{s2}). Those lengths are measured where the predicted wall shear stress profiles $\tau_{xy} = \mu \partial u_x / \partial y$ vanish.

Results

The most optimal DNN can predict the extents of the primary recirculation zone with a minimum of 0.5% **validation accuracy** and a **generalization accuracy** ranging between 5.8% and 14.4%.

As in Figure 2, a DNN trained on 2D numerical simulation data for Re < 400 - where results align within 5% of experimental data – can produce **generalization predictions** consistent with experimental results in the range of 400<Re<920, where the flow becomes **three-dimensional**.

With a **computing time of ~0.6 s**, the **DNNs** are **12.5 to 14 times faster** than a non-linear stationary PARDISO solver on the same mesh within COMSOL Multiphysics®.

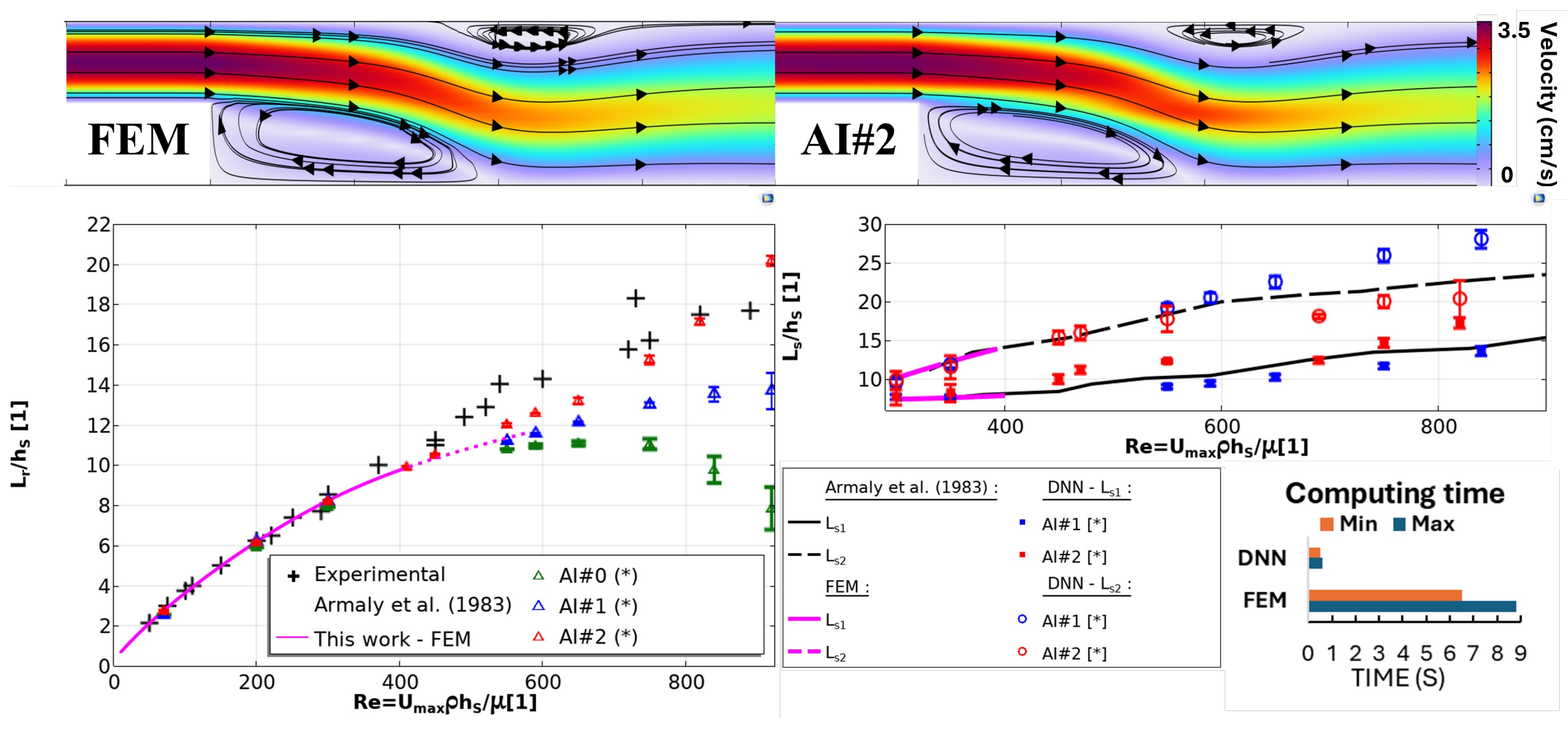

FIGURE 2. Predictions of the neural networks against reference data, and computing time performance.

REFERENCES

1. Y. Shenghong, “Two dimensional backward facing single step flow preceding an automotive air-filter”, PhD Thesis, Oklahoma State University, 2000.
2. B. F. Armaly, F. Durst, J. C. F. Pereira and B. Schönung,“Experimental and theoretical investigation of backward-facing step flow”, *Journal of Fluid Mechanics*, vol. 127, p. 473–496, 1983.
3. B. Zajec, M. Matkovič, N. Kosanič, J. Oder, B. Mikuž, J. Kren and I. Tiselj, “Turbulent Flow over Confined Backward-Facing Step: PIV vs. DNS”, *Applied Sciences*, vol. 11, no. 22, p. 10582, 2021.

COMSOL
Certified Consultant

ProtoSTEP®
Forward
R&D SOLUTIONS

Excerpt from the Proceedings of the COMSOL Conference 2024 Florence