Improvement of RANS models by machine learning for a bump configuration

Pedro Stefanin Volpiani[1,*], Raphaella Fusita Bernardini[1,2], Lucas Franceschini[2,3]

*pedro.stefanin_volpiani@onera.fr

2022 Symposium on Turbulence Modeling: Roadblocks, and the Potential for Machine Learning

July 27 - 29, 2022 - Suffolk, USA

ONERA

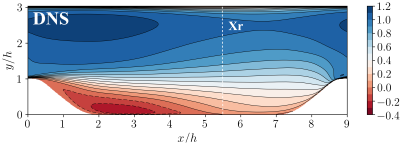
THE FRENCH AEROSPACE LAB

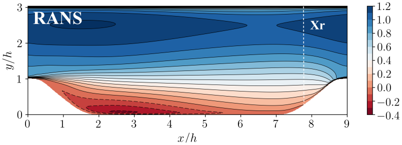
[1]ONERA/DAAA, [2]University of São Paulo, [3]University of Twente

Motivation

RANS simulations are widely used in engineering but they lack accuracy.

- flows with adverse pressure gradient, large separations, curvature, swirl, ...





Periodic hill configuration at Re=2800 : mean streamwise velocity field.

Introduction

Motivation

RANS simulations are widely used in engineering but they lack accuracy.

- flows with adverse pressure gradient, large separations, curvature, swirl, ...

Goal

Improve predicted capabilities of classic turbulence models

→ 2021 : Data assimilation + Machine learning (Boussinesq correction)

→ 2022 : Machine learning (Eddy-viscosity correction)

Introduction

Motivation

RANS simulations are widely used in engineering but they lack accuracy.

- flows with adverse pressure gradient, large separations, curvature, swirl, ...

Goal

Improve predicted capabilities of classic turbulence models

→ 2021 : Data assimilation + Machine learning (Boussinesq correction)

→ 2022 : Machine learning (Eddy-viscosity correction)

Requirements

→ High fidelity test cases, reflecting critical physics

Recap of 2021 work

Solve the exact equations : $\mathcal{R}_e(u_e(\mathbf{x}, t)) = 0$

Recap of 2021 work

Solve the exact equations : $\mathcal{R}_e(u_e(\mathbf{x}, t)) = 0$

Solve the model equations : $\mathcal{R}_m(u_m(\mathbf{x}, t)) = 0$

Recap of 2021 work

Solve the exact equations : $\mathcal{R}_e(u_e(\mathbf{x}, t)) = 0$

Solve the model equations : $\mathcal{R}_m(u_m(\mathbf{x}, t)) = 0$

Perform the DA to correct the discrepancies : $\mathcal{R}_\alpha(u_\alpha(\mathbf{x}, t), \alpha(\mathbf{x}, t)) = 0$, where α is the correction term

Recap of 2021 work

Solve the exact equations : $\mathcal{R}_e(u_e(\mathbf{x}, t)) = 0$

Solve the model equations : $\mathcal{R}_m(u_m(\mathbf{x}, t)) = 0$

Perform the DA to correct the discrepancies : $\mathcal{R}_\alpha(u_\alpha(\mathbf{x}, t), \alpha(\mathbf{x}, t)) = 0$, where α is the correction term

Build a NN to construct the correction term as a function of available flow quantities

Recap of 2021 work

Solve the exact equations : $\mathcal{R}_e(u_e(\mathbf{x}, t)) = 0$

Solve the model equations : $\mathcal{R}_m(u_m(\mathbf{x}, t)) = 0$

Perform the DA to correct the discrepancies : $\mathcal{R}_\alpha(u_\alpha(\mathbf{x}, t), \alpha(\mathbf{x}, t)) = 0$, where α is the correction term

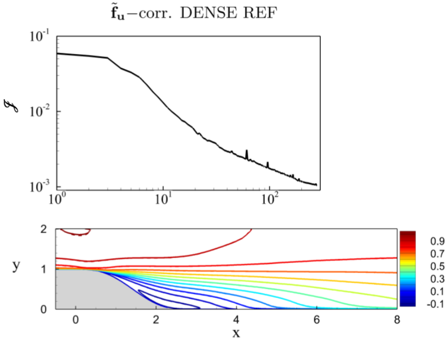
Build a NN to construct the correction term as a function of available flow quantities

Computations are performed using the NN augmented turbulence model

Data assimilation following Franceschini et al. (2020, PRF)

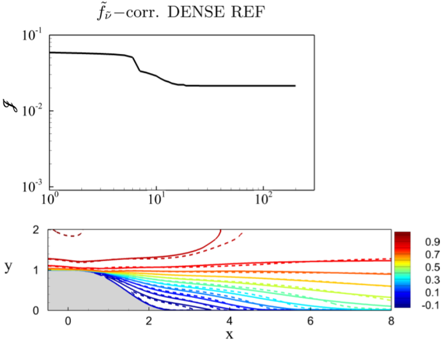
- Boussinesq correction :

$$\frac{\partial u_i u_j}{\partial x_j} = -\frac{\partial p}{\partial x_i} + \frac{\partial(2\nu S_{ij})}{\partial x_j} + \frac{\partial \tau_{ij}^{SA}}{\partial x_j} + f_{u_i}$$



- Eddy-viscosity correction :

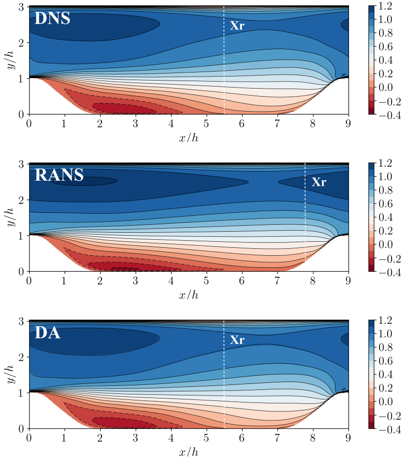
$$u_j \frac{\partial \tilde{\nu}}{\partial x_j} = P - D + T + f_{\tilde{\nu}}$$



Data assimilation - Volpiani et al. (2021, PRF)

Periodic hill configuration ($Re_b = 2800$)

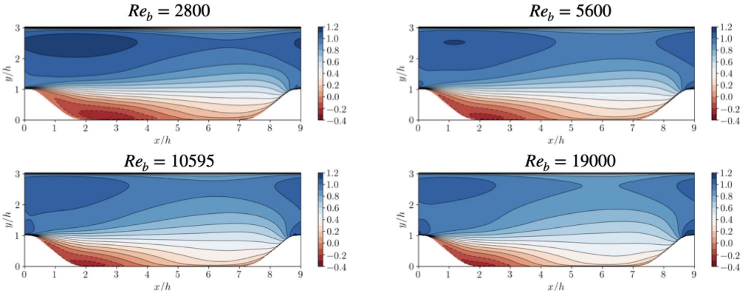
Mean streamwise velocity field



Machine learning strategy - Volpiani et al. (2021, PRF)

Database of training flows to predict flow past periodic hills

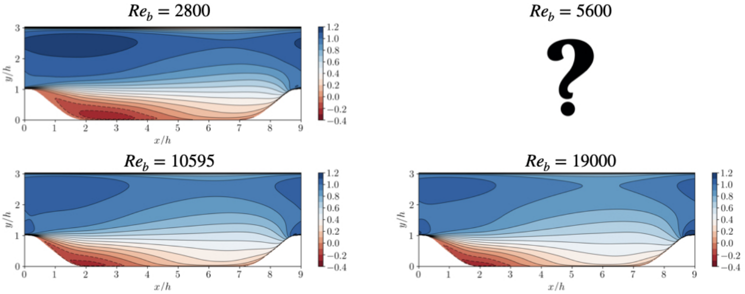
Training flow scenario	Selected cases	Fit on training data only	Fit on entire data without rotation
Scenario I	PH-2800, PH-10595, PH-19000	96.5 %	95.6 %
Scenario II	PH-2800, PH-5600, PH-10595	96.2 %	93.5 %



Machine learning strategy

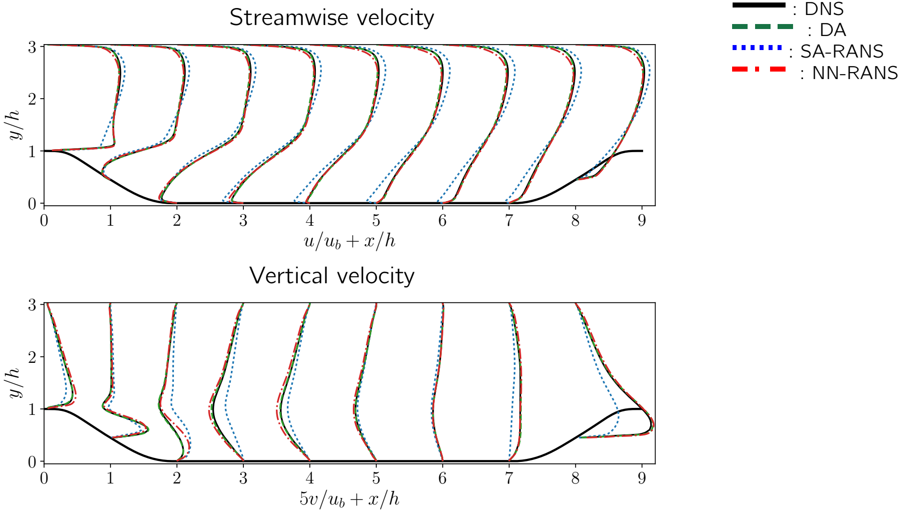
Database of training flows to predict flow past periodic hills

Training flow scenario	Selected cases	Fit on training data only	Fit on entire data without rotation
Scenario I	PH-2800, PH-10595, PH-19000	96.5 %	95.6 %
Scenario II	PH-2800, PH-5600, PH-10595	96.2 %	93.5 %

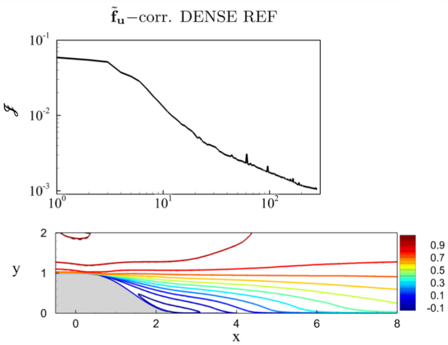


RANS using a neural network-based model

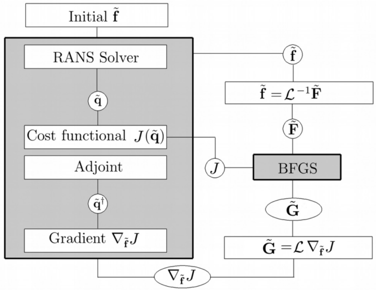
Interpolation in Reynolds number : scenario I is used to predict flow at $Re_b = 5600$



Data assimilation following Franceschini et al. (2020, PRF)



Assimilation of velocity measurements based on the volume force f_{u_i}



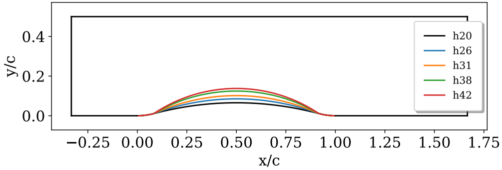
Coupling between the optimization algorithm (BFGS) and the fluid solver.

Eddy-viscosity correction

RANS equations :

$$\frac{\partial \bar{u}_i}{\partial x_i} = 0, \qquad \frac{\partial \bar{u}_i \bar{u}_j}{\partial x_j} = -\frac{\partial \bar{p}}{\partial x_i} + \frac{\partial}{\partial x_j}\left[2(\nu + \nu_t^{SA} + \Delta\nu_t) S_{ij}\right]$$

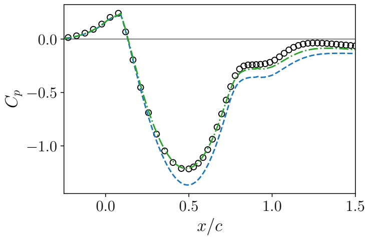
- ν_t^{SA} is determined by solving the one equation Spalart-Allmaras (SA) turbulence model
- $\Delta\nu_t$ is determined using the LES statistical data : $\nu_t^{LES} = \frac{-\overline{u_i' u_j'}\, \partial_j \overline{u_i}}{2 S_{ij} S_{ij}} \approx \frac{\max\left(0, -\overline{u_i' u_j'}\, \partial_j \overline{u_i}\right)}{\max\left(0, 2 S_{ij} S_{ij}\right) + \epsilon}$

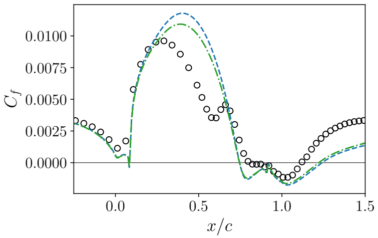


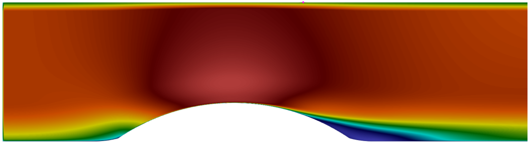
Family of bumps from Matai & Durbin (JFM, 2019).

Baseline RANS-SA simulation for the flows over a family of bumps

Discussion on boundary conditions : slip wall, as LES (shorter domain), LES bump h42.







Streamwise velocity for bump h42 from Matai & Durbin (JFM, 2019).

Eddy-viscosity correction

RANS equations :

$$\frac{\partial \bar{u}_i}{\partial x_i} = 0, \qquad \frac{\partial \bar{u}_i \bar{u}_j}{\partial x_j} = -\frac{\partial \bar{p}}{\partial x_i} + \frac{\partial}{\partial x_j}[2(\nu + \nu_t^{SA} + \Delta\nu_t)S_{ij}]$$

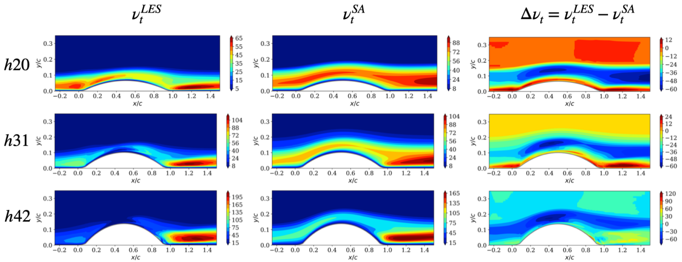
- $\Delta\nu_t$ is determined using the LES statistical data : $\nu_t^{LES} = \frac{-\overline{u_i' u_j'}\,\partial_j \overline{u_i}}{2S_{ij}S_{ij}} \approx \frac{\max\left(0,-\overline{u_i' u_j'}\,\partial_j \overline{u_i}\right)}{\max\left(0,2S_{ij}S_{ij}\right)+\epsilon}$

Eddy-viscosity correction

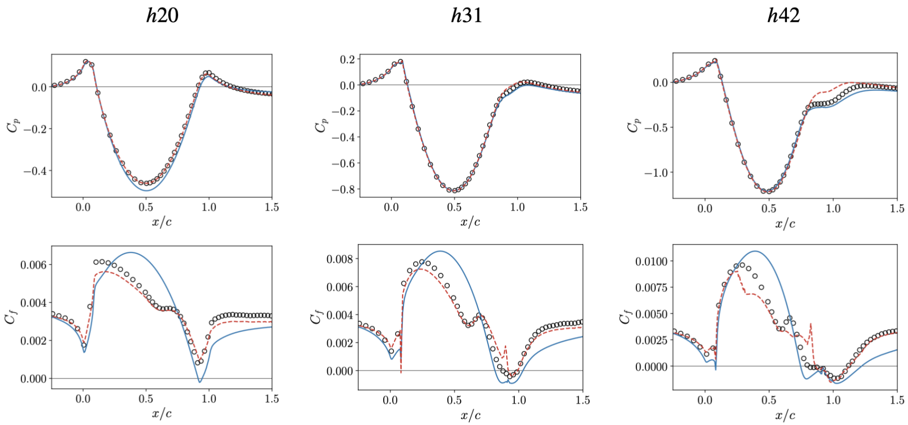
RANS equations :

$$\frac{\partial \bar{u}_i}{\partial x_i} = 0, \qquad \frac{\partial \bar{u}_i \bar{u}_j}{\partial x_j} = -\frac{\partial \bar{p}}{\partial x_i} + \frac{\partial}{\partial x_j}\left[2(\nu + \nu_t^{SA} + \Delta\nu_t) S_{ij}\right]$$

- $\Delta\nu_t$ is determined using the LES statistical data : $\nu_t^{LES} = \frac{-\overline{u_i' u_j'}\, \partial_j \overline{u_i}}{2 S_{ij} S_{ij}} \approx \frac{\max\left(0, -\overline{u_i' u_j'}\, \partial_j \overline{u_i}\right)}{\max\left(0, 2 S_{ij} S_{ij}\right) + \epsilon}$



Eddy-viscosity correction



Corrected C_p and C_f profiles : RANS-SA, RANS-ν_t^{LES}.

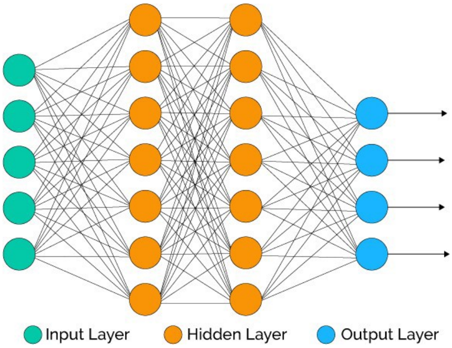
Machine learning strategy

Input layer :

Feature	Description	Formula
q_1	Q-criterion	$\frac{\|\|\boldsymbol{\Omega}\|\|^2 - \|\|\mathbf{S}\|\|^2}{\|\|\boldsymbol{\Omega}\|\|^2 + \|\|\mathbf{S}\|\|^2}$
q_2	Ratio of pressure normal stresses to shear stresses	$\frac{\sqrt{\frac{\partial \bar{p}}{\partial x_k}\frac{\partial \bar{p}}{\partial x_k}}}{\sqrt{\frac{\partial \bar{p}}{\partial x_k}\frac{\partial \bar{p}}{\partial x_k} + \frac{1}{2}\frac{\partial \bar{u}_k^2}{\partial x_k}}}$
q_3	Gorle et al. marker	$\frac{\left\|\bar{u}_i \bar{u}_j \frac{\partial \bar{u}_i}{\partial x_j}\right\|}{\left\|\bar{u}_i \bar{u}_j \frac{\partial \bar{u}_i}{\partial x_j}\right\| + \sqrt{\bar{u}_l \bar{u}_l \bar{u}_i \frac{\partial \bar{u}_i}{\partial x_j} \bar{u}_k \frac{\partial \bar{u}_k}{\partial x_j}}}$
q_4	Streamline pressure gradient	$\frac{\bar{u}_k \frac{\partial \bar{p}}{\partial x_k}}{\left\|\bar{u}_k \frac{\partial \bar{p}}{\partial x_k}\right\| + \sqrt{\frac{\partial \bar{p}}{\partial x_k}\frac{\partial \bar{p}}{\partial x_k} \bar{u}_i \bar{u}_i}}$
q_5	Viscosity ratio	$\frac{\nu_t}{\nu_t + 100\nu}$
q_6	SA ratio of production to destruction	$\frac{c_{b1}\tilde{S}\tilde{\nu}}{\left\|c_{b1}\tilde{S}\tilde{\nu}\right\| + c_{w1} f_w \left(\frac{\tilde{\nu}}{d}\right)^2}$
q_7	SA ratio of production to diffusion	$\frac{c_{b1}\tilde{S}\tilde{\nu}}{\left\|c_{b1}\tilde{S}\tilde{\nu}\right\| + \frac{c_{b2}}{\sigma}\frac{\partial \tilde{\nu}}{\partial x_k}\frac{\partial \tilde{\nu}}{\partial x_k}}$
q_8	Turbulence intensity	$\frac{k_{qcr}}{k_{qcr} + \frac{1}{2}\bar{u}_i^2}$

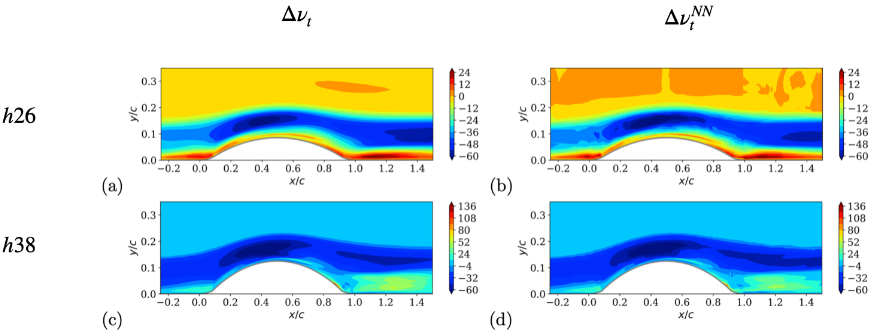
Hidden layer : $4 \times 80 neurons$

Output layer : $\Delta\nu_t$ or ν_t^{LES}



Predicting the viscosity discrepancy $\Delta\nu_t$ using NN1

Training cases : h20, h31, h42 Validation cases : h26, h38



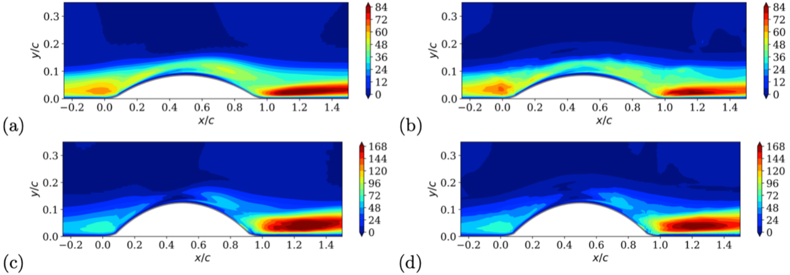
Predicting the viscosity discrepancy ν_t^{LES} using NN2

Training cases : h20, h31, h42 Validation cases : h26, h38

ν_t^{LES} ν_t^{NN}

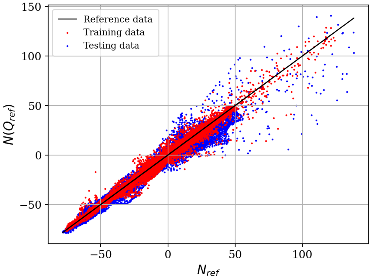
h26

h38

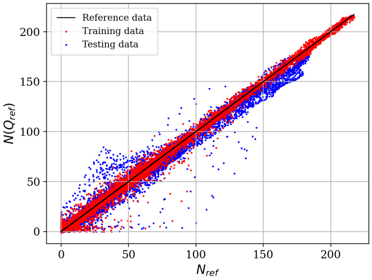


Comparison between NN1 vs NN2

NN1 - $\Delta\nu_t^{NN}$

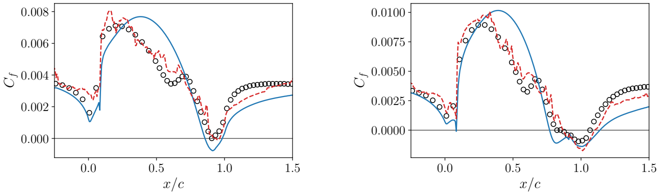


NN2 - ν_t^{NN}



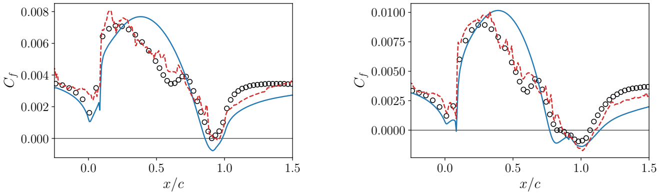
A posteriori results using NN1 and NN2

NN1 - $\Delta\nu_t^{NN}$

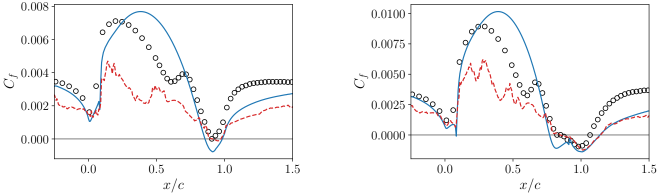


A posteriori results using NN1 and NN2

NN1 - $\Delta\nu_t^{NN}$

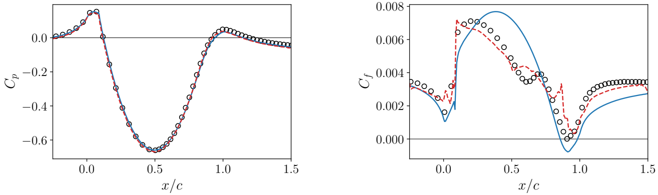


NN1 - $\Delta\nu_t^{NN}$ no treatment

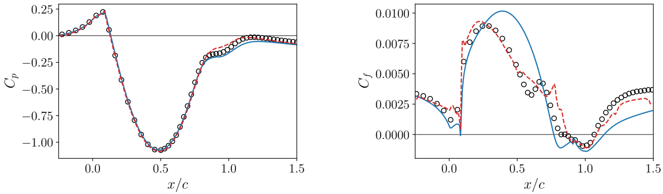


A posteriori results using NN1 and NN2

NN2 - ν_t^{NN}



h26



h38

ONERA THE FRENCH AEROSPACE LAB

Final remarks

Conclusions

- In the past, we employed DA+ML to improve RANS models
- This strategy gives accurate results but it is quite complex and time consuming
- More recently, we employed ML to correct directly the unknown eddy-viscosity term in the RANS equations
- Advantages : simple, fast, no need to transport any turbulent variables
- Although not perfect, the NN-based model improved C_p and C_f predictions
- **Machine learning-based turbulence models can be used to improve CFD capabilities**

Publication

- Volpiani et al. (2021). Machine learning-augmented turbulence modelling for RANS simulations of massively separated flows. *Physical Review Fluids*.
- Volpiani, Bernardini & Francesquini (2022). Neural network-based eddy-viscosity correction for RANS simulations of flows over bi-dimensional bumps. *International Journal of Heat and Fluid Flow*.