



Recent efforts in Machine Learning for RANS modelling of separated flows

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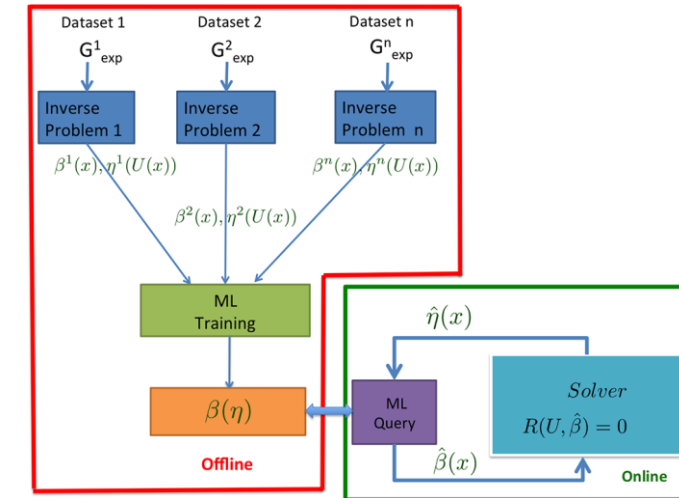


Acknowledgements



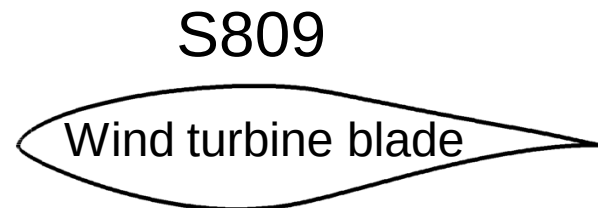
- **Mujeeb Malik – Sponsor/RCA Project Lead**
- **Chris Rumsey – Primary collaborator/recent “Heavy Lifting”**
- **Jan-Rene Carlson – FUN3D support**
- **Li Wang – Adjoint/FUN3D support**

- NASA funded University of Michigan to explore potential of ML for turbulence modeling improvement: Singh, Medida, and Duraisamy (AIAA J 55(7):2215-2227, 2017)
 - Field inversion** (find an optimized “ β ” field that improves the Spalart-Allmaras (SA) model for given training cases) $\frac{Dv}{Dt} = \beta(x, y, z)P(v, U) - D(v, U) + T(v, U)$
 - Machine learning** (use the training cases to learn β as a function of local nondimensional field variables)
- Current NASA (under RCA) effort is to internalize and evaluate the above approach
- Make use of NASA CFD code FUN3D’s existing adjoint capability to perform the field inversion
 - Find β by minimizing an objective function based e.g. on desired lift coefficient
- Note: there are other ML-based efforts described in the literature
 - This particular approach was chosen to make a start; there is no guarantee that it is the best path forward

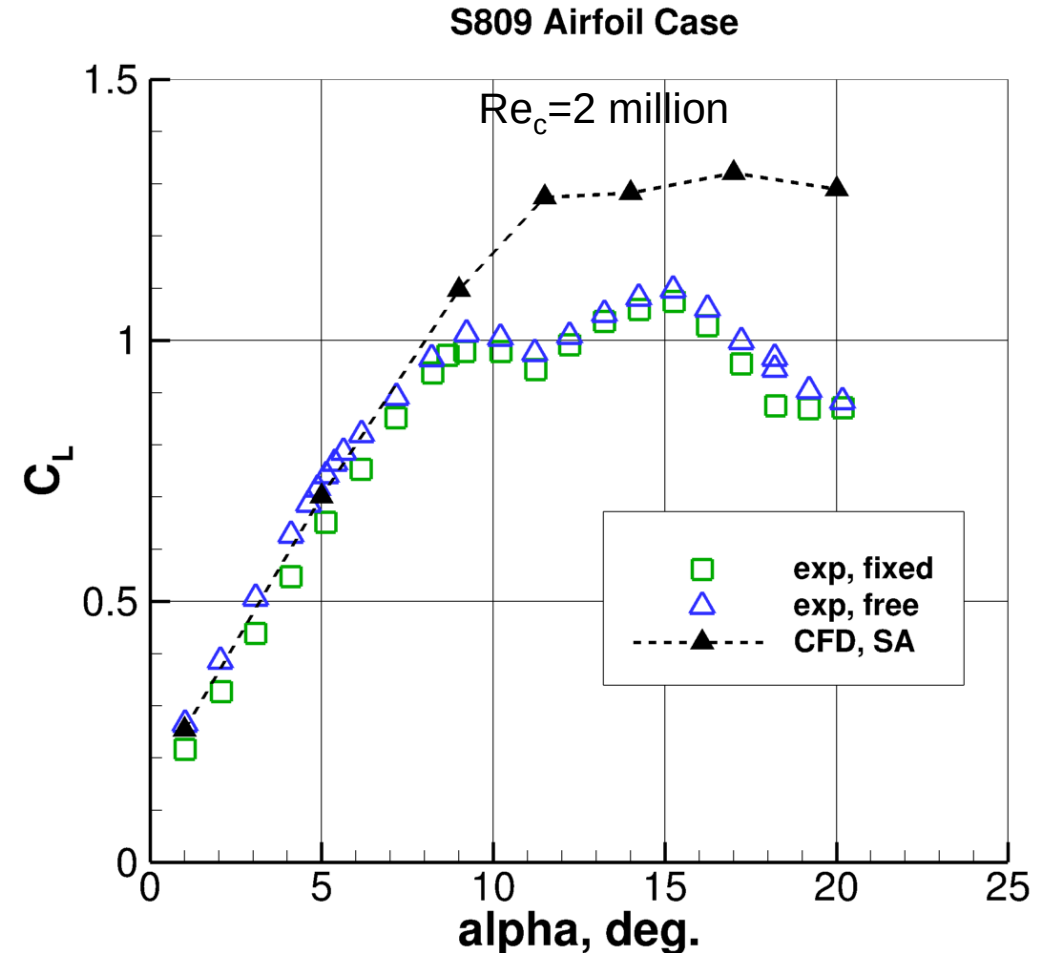


Singh et al. (2017)

- **Field inversion** for SA implemented in FUN3D (via Adjoint), based on target C_L
 - Test case: S809 2D airfoil
(following Singh et al. 2017)
- **Machine learning** (outside of FUN3D)
- **Prediction** – Implement NN model back into flow solver (FUN3D)
- **Focus** on feature selection to maximize generalizability

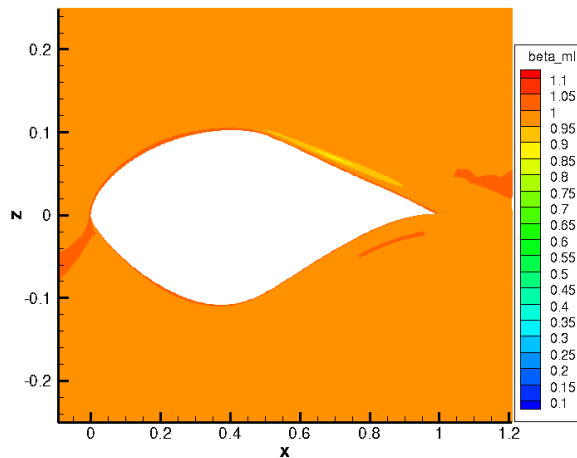


Goal: improve model predictions at high alpha (separated flow)



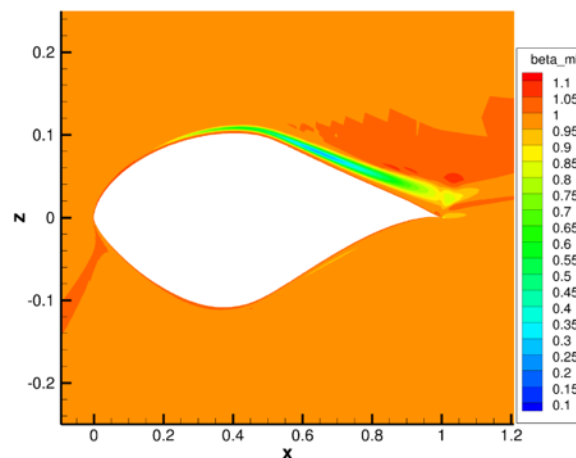
fixed=fixed transition with tripping; free=no tripping

AoA=5 deg



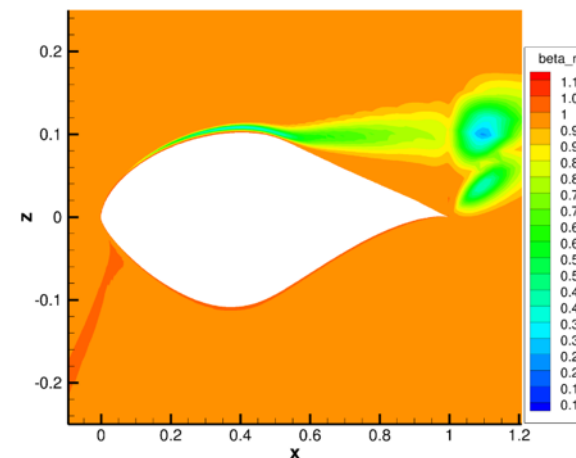
min=0.80, max=1.02

AoA=9 deg



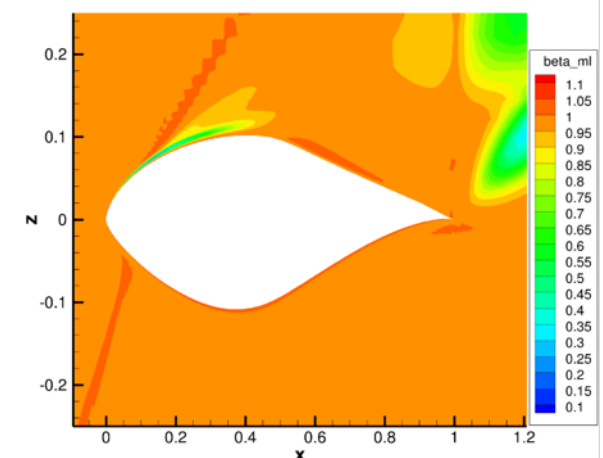
min=0.24, max=1.13

AoA=14 deg



min=0.23, max=1.12

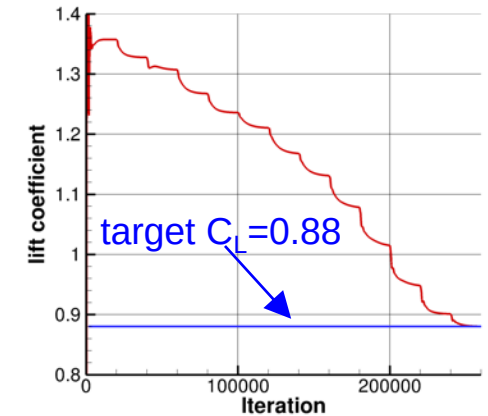
AoA=20 deg



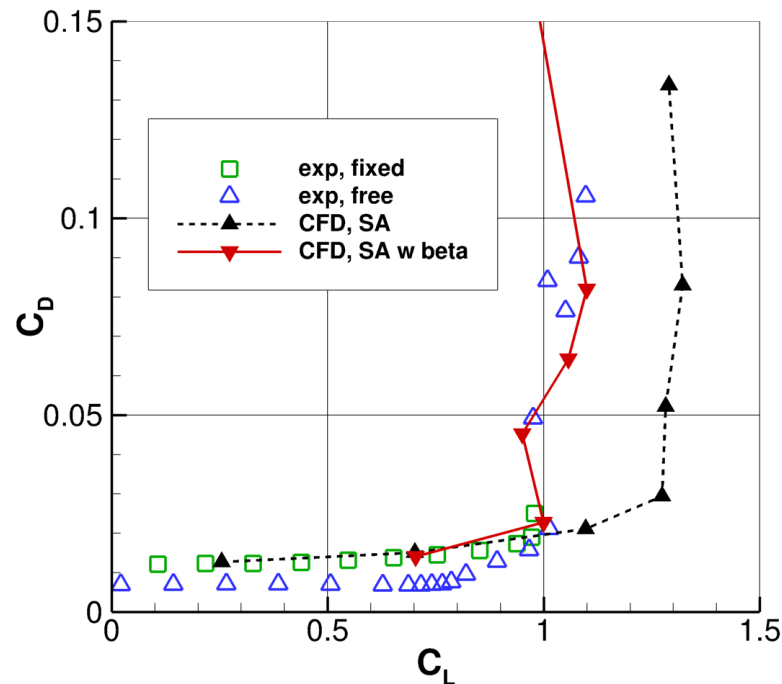
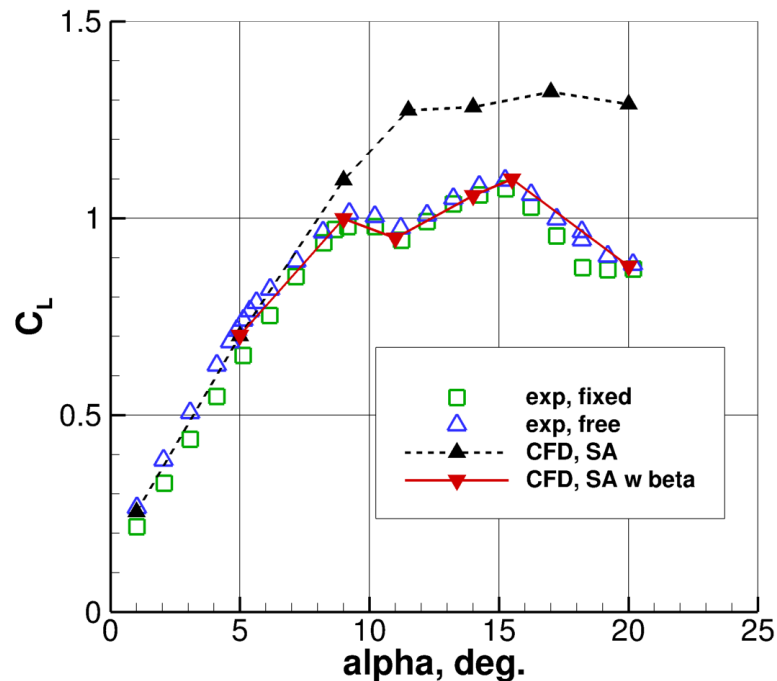
min=0.21, max=1.25

- C_L in good agreement with the experimental results
- Even the drag and C_p predictions significantly improve

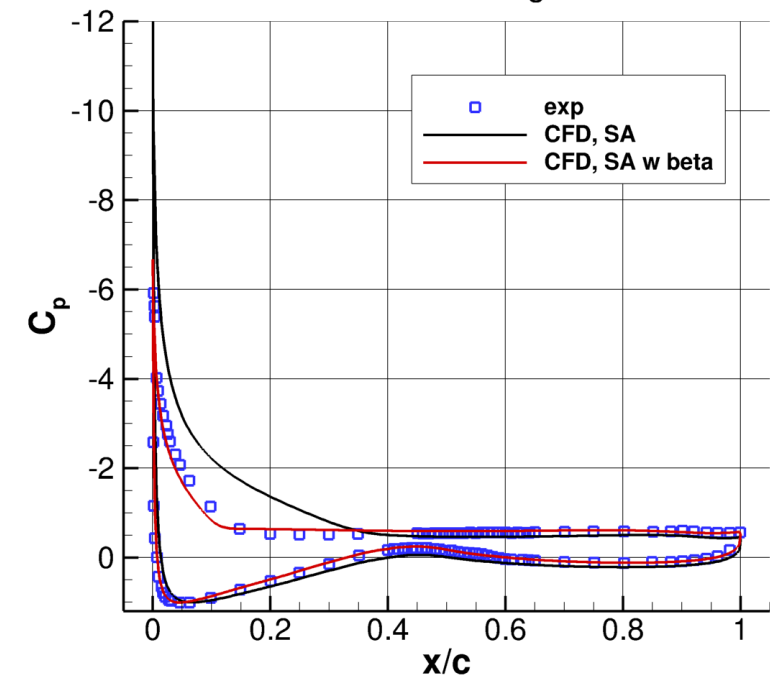
C_L progress toward target



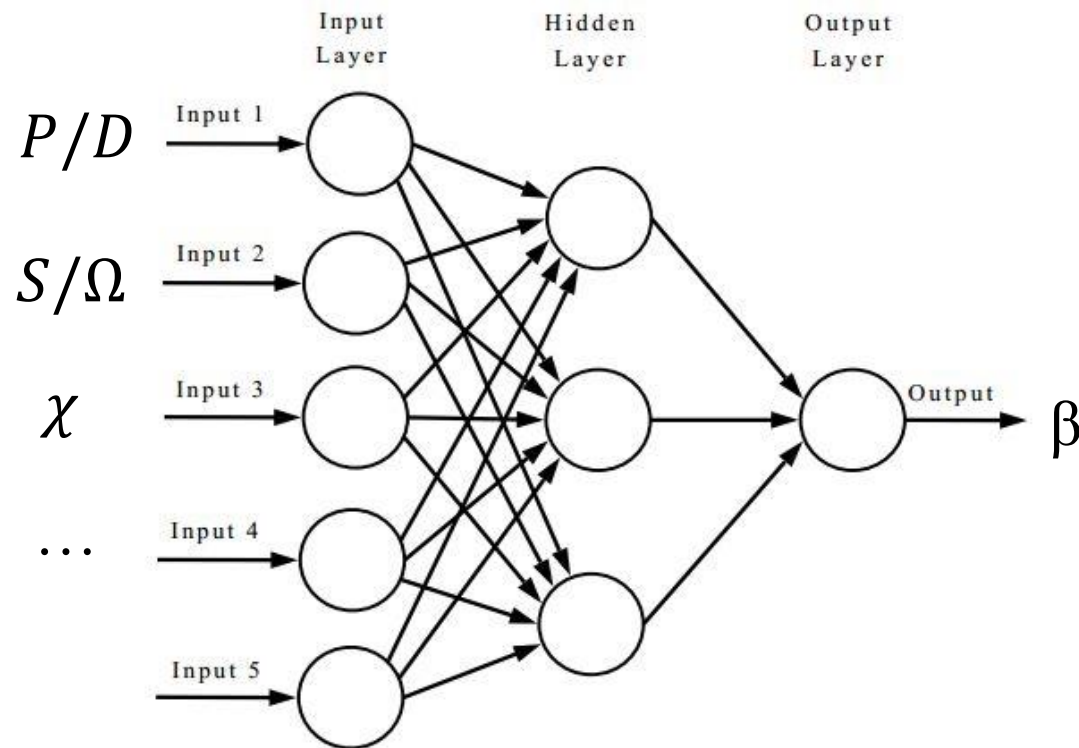
S809 Airfoil Case



AoA=20 deg



- Select nondimensional field “features”
 - e.g., P/D , S/Ω , χ , ...
- Employ a neural network (NN) algorithm to “learn” β as a function of these features

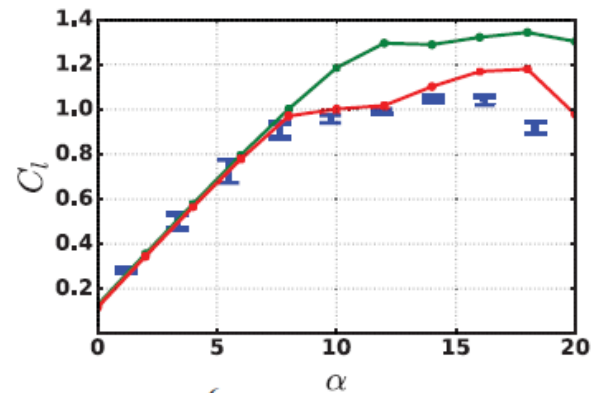


Choices:

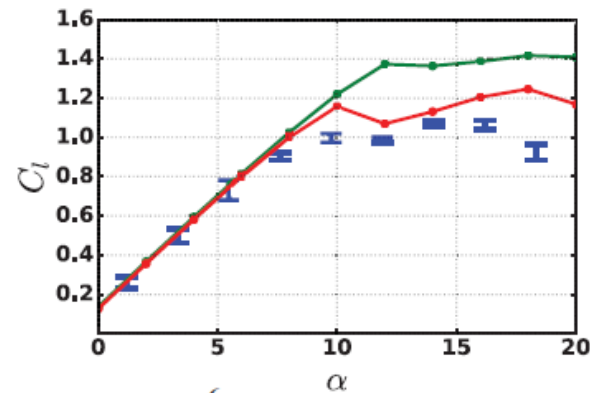
- Which/how many training cases to use?
- How many hidden layers?
- How many nodes per layer?
- **Which features to use?**

Currently somewhat of an art

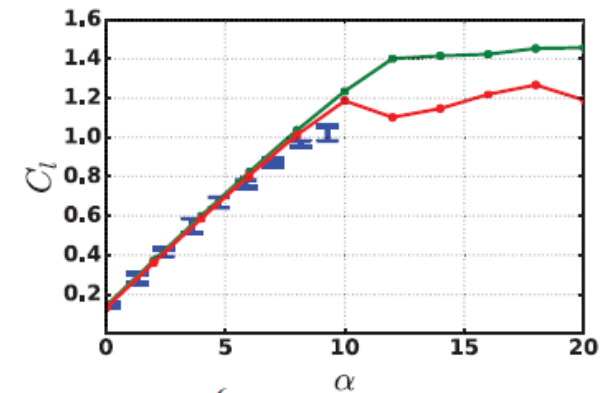
Singh et al. (2017)



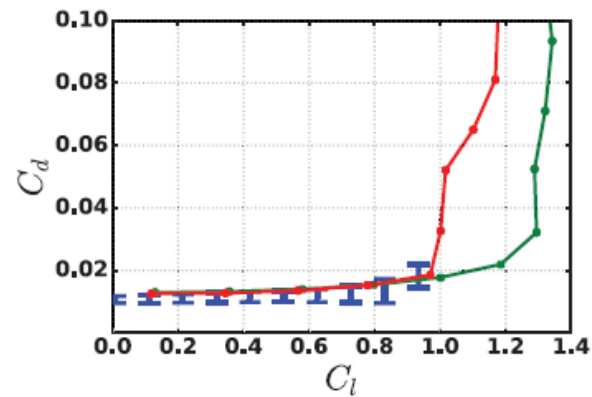
a) $Re = 1 \times 10^6$



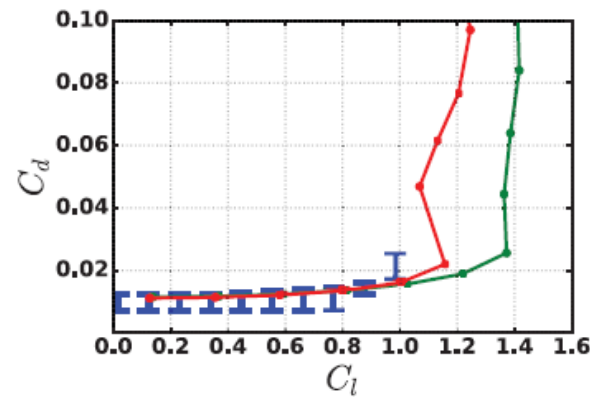
b) $Re = 2 \times 10^6$



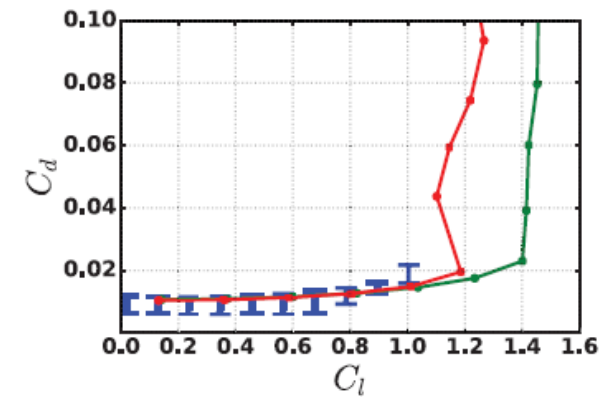
c) $Re = 3 \times 10^6$



d) $Re = 1 \times 10^6$



e) $Re = 2 \times 10^6$



f) $Re = 3 \times 10^6$

Green: Base SA Model

Red: NN Model

Symbols: exp data

Note: The 3 million Re case was not included in the training data



Next steps



- Attempt to answer questions, gain experience, and possibly see path toward new ideas
 - How does the choice of features, hidden layers, nodes, etc. influence the training?
 - What causes success/failure in the training step?
 - How does one decide when a trained model is “good enough”?
 - From what source (exp, DNS, LES, RANS?) and what cases should the training data optimally come from?
 - How “far away” from the training data will the NN work?
 - Which features are most appropriate, in terms of maximizing generality of ML-generated RANS models for aerospace CFD?



Upcoming Turbulence Modelling/ML Workshop



- “*Turbulence Modeling: Roadblocks, and the Potential for Machine Learning*”
 - Originally scheduled for March 2021, to correspond to Philippe Spalart’s 65th birthday.
New date: 25-27 March 2022
 - Hampton Roads Virginia: Lockheed Martin “Lighthouse”, Suffolk, VA
- Scope of the Workshop
 - Identify critical issues for RANS models, and possible ways forward
 - “*Collaborative Testing Challenge*” for data-driven RANS models
 - Apply your ML-assisted model to a **range** of canonical NASA test cases
- Points of contact
 - Chris Rumsey c.l.rumsey@nasa.gov
 - Gary Coleman g.n.coleman@nasa.gov
- Further details: <https://turbmodels.larc.nasa.gov/turb-prs2021.html>