ASCENT Project 075

Improved engine fan broadband noise prediction capabilities

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Cost Share Partner: BU, RTRC, AARC

Objective:

Improve low-order (LO) models for the prediction of fan broadband interaction noise by addressing gaps in existing methods using both computation and experimentation. The main gaps being considered are a LO model for the inflow to an exit guide vane and full-scale validation of the LO exit guide vane response.

Project Benefits:

Elimination of time-consuming, high-fidelity simulations or prototype development and testing in order to assess broadband noise levels created by high bypass turbofans.

Research Approach:

- Develop a surrogate model for a fan wake using machine learning. Create the necessary training data and compare different machine learning methods. Determine both the mean and turbulence wake profiles upstream of the exit guide vane using only rotor-based information.

- Test the current LO exit guide vane response method's ability to predict the broadband noise associated with a full-scale case using available experimental data.

Major Accomplishments (to date):

- Data set : 4 geoms, 7 rotor speeds, 7 mass flows
- ML methods for mean flow wake, TKE, ω
  - SDT related geometries
  - Single input -> single output ML: 3 methods tested
    - Spline, XGBOOST/decision tree, DNN
  - Multi output ML : CNN started

Future Work / Schedule:

- Winter: LO response tested on full-scale rig data

  CLEEN I config
- Winter/spring: ML
  - New geometries -> larger data set
  - Additional input parameters
  - ML for rotor force distribution
  - Further CNN development

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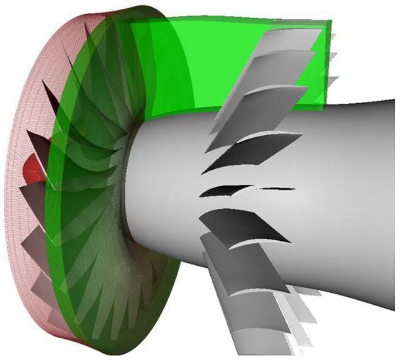
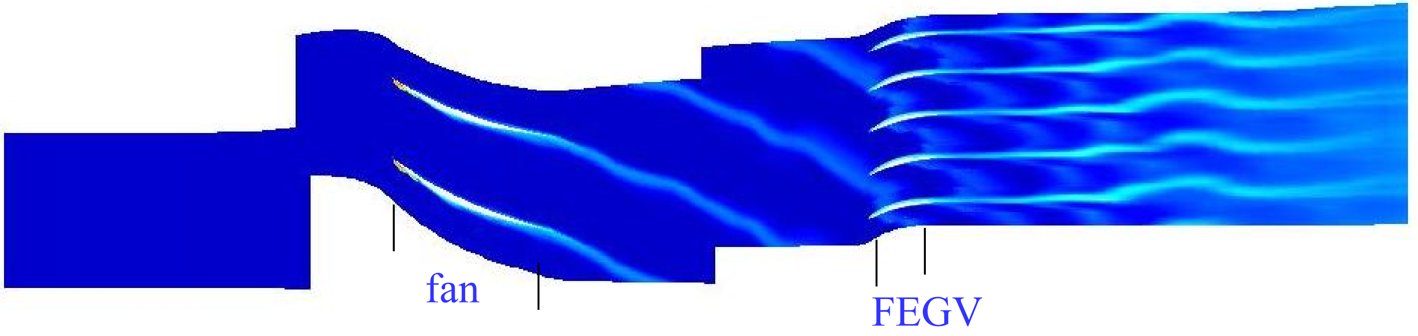
Fan broadband noise background

Largest broadband contributor in a fan stage is from rotor wake interaction with FEGV

(This also produces the tonal noise)





- Low-order methods aimed at assisting in the design phase use :
  - Information about the rotor wake turbulence intensity and lengthscale (as well as mean flow)
  - Then the response of the FEGV is computed and subsequently the noise produced by the interaction
- Rotor wake info currently taken from simulation or experiment …
  - Method not fully “low-order”

Our project

Main part:

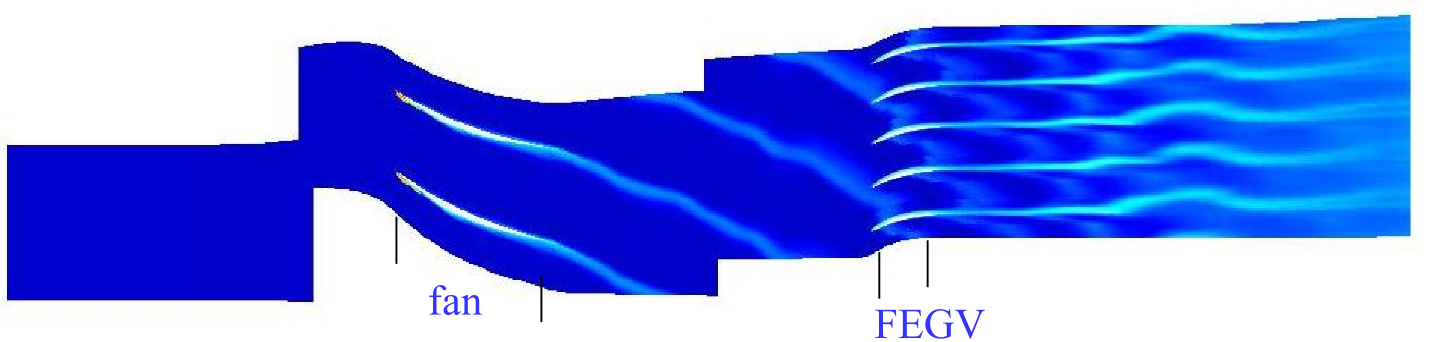
Create a surrogate model for the rotor wake flow (eliminating need for computation or experiment in order to define input for the low-order FEGV calculation)

Use machine learning

End goal: provide fan geometry, RPM, mass flow and perhaps some other information together with duct geometry and have the surrogate model provide the mean flow and turbulence intensity and length scale just upstream of the FEGV

Secondary part:

Improve the low-order FEGV response method: full scale validation, relaxation of some assumptions



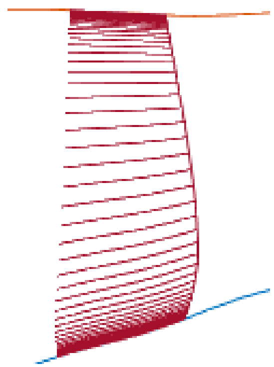
Machine learning

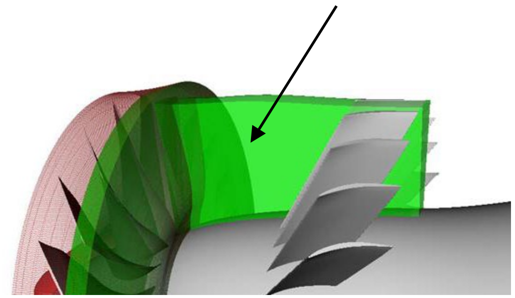
We have considered 2 basic methods so far

Method 1: single output

Define rotor geometry on %radial strips:
- chord,
- stagger,
- position of t.e.
- t.e. bdy layer thickness

Give RPM, mass flow





Provide flow values on portion of NxMxP grid in the gap region
- Streamwise velocity magnitude
- TKE (k)
- Turbulent dissipation (ε or ω)

Predict flow values on ordered grid points
- Streamwise velocity mag
- TKE (k)
- Turbulent dissipation

Used splines, MARS, XGBOOST with decision tree, DNN

Tested necessary values of N, M, P (3D grid in gap)

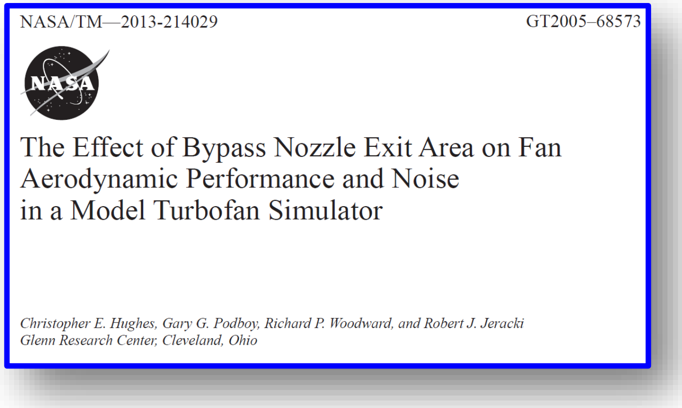
Tested method for selecting which data to use for training/testing

Random selection out of N, M, P (what %: 80% train, 20% test, etc.)

Leave out entire N (axial locations), leave out entire mass flow cases, etc.

Database for the ML thus far

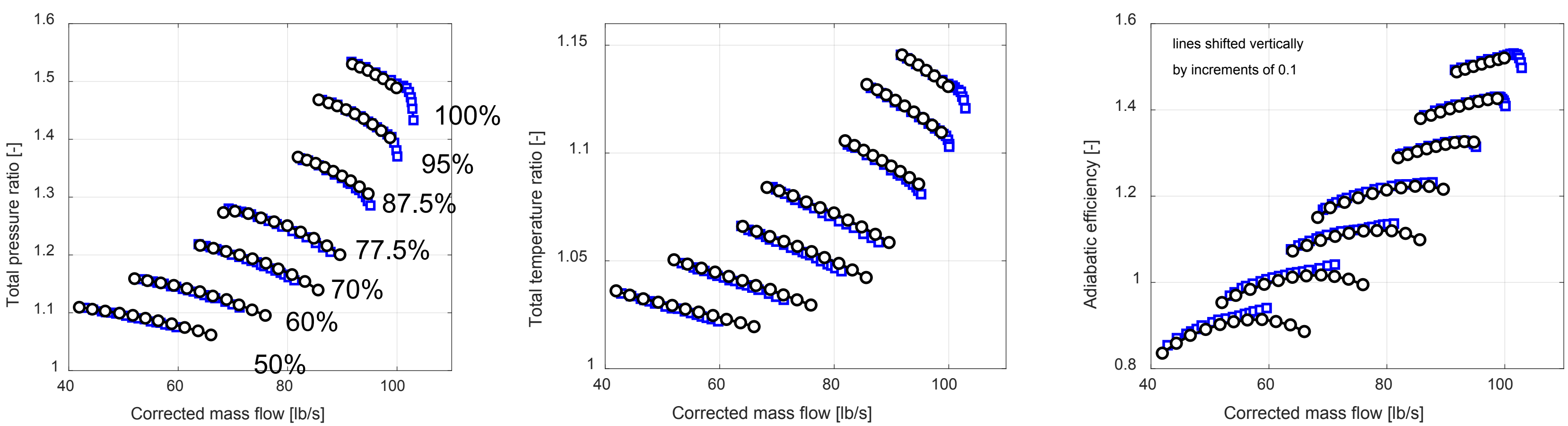
- Use RANS (k-ω), rotor alone simulations in rotor frame
- Geometries : based on NASA SDT
  - CAD (cold), 7808 RPM (hot), 11607 RPM (hot), 12657 RPM (hot)
- 7 RPM : 50%, 60%, 70%, 77.5%, 87.5%, 95%, 100%
- 7-10 mass flow rates at each RPM
- Total of 268 cases


NASA/TM—2013-214029 GT2005–68573

The Effect of Bypass Nozzle Exit Area on Fan Aerodynamic Performance and Noise in a Model Turbofan Simulator

Christopher E. Hughes, Gary G. Podboy, Richard P. Woodward, and Robert J. Jeracki
Glenn Research Center, Cleveland, Ohio

Example: SDT cold. EXP data (digitized from NASA TM, fan alone performance)

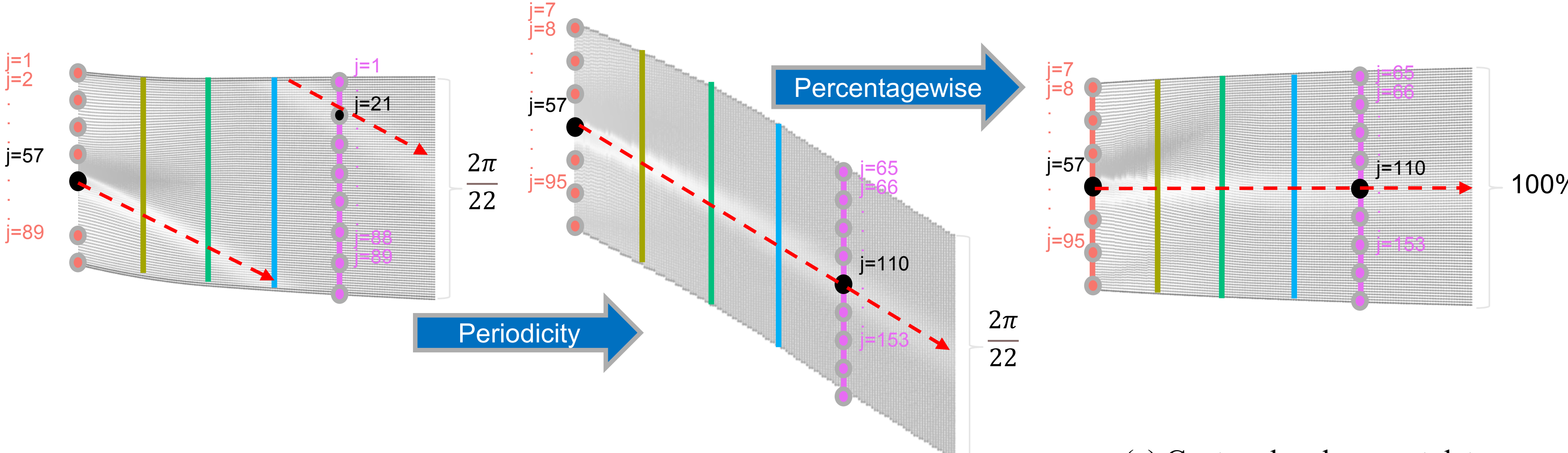


ML method I

2 step process for the machine learning

1st : learn functions related to rectification of the wake

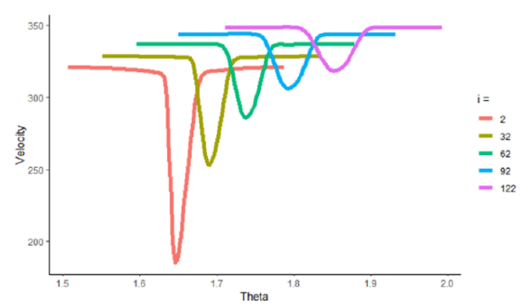
2nd: learn the flow values in the wake

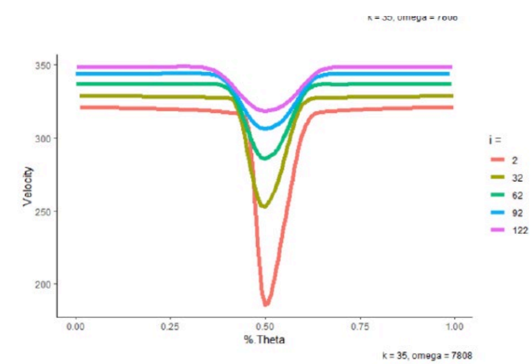


(a) Original data (at fixed radial %)

(b) Centered data

(c) Centered and percent data





ML method I

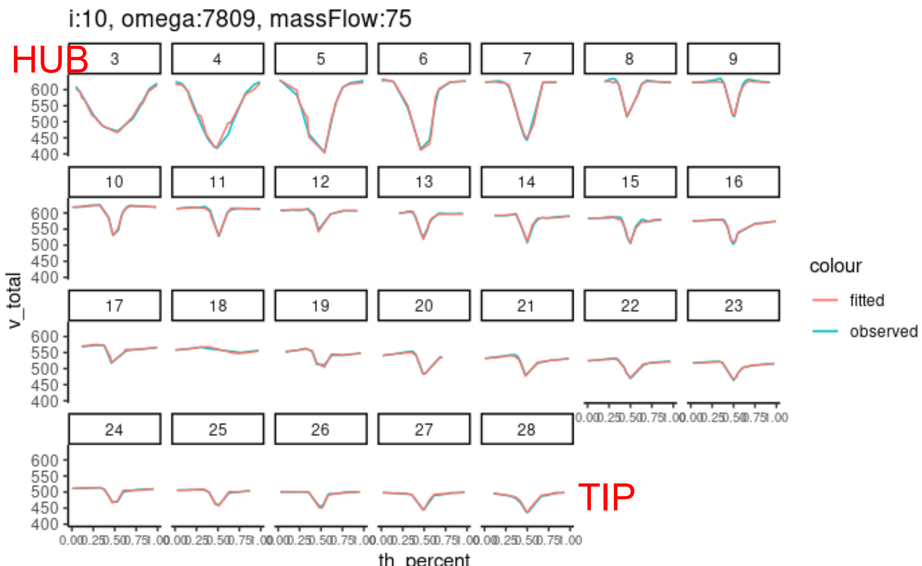
Example: streamwise velocity, XGBOOST

When randomly use 80% of NxMxP gap points

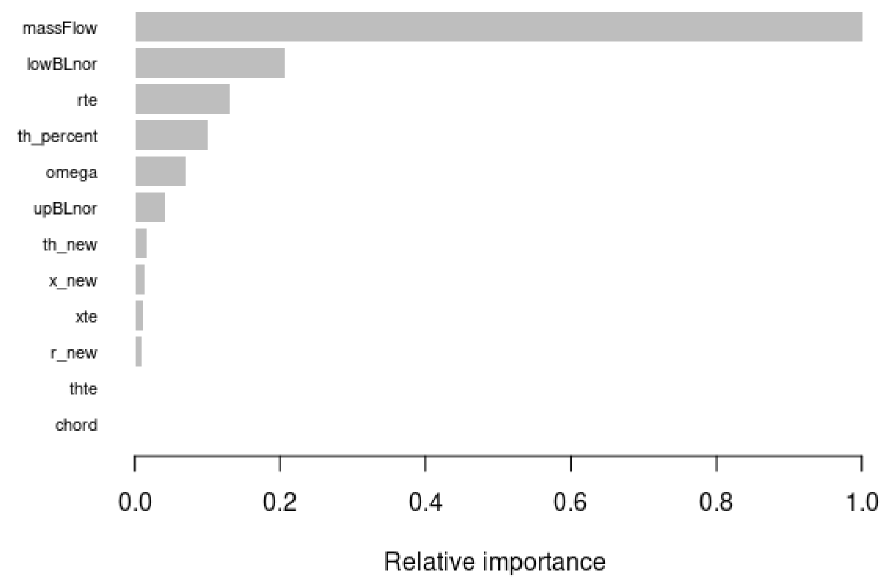
Very good reconstructions of points not used.

- Model: v_total ~ omega + r_te + r_new + th_te + th_new + x_te + th_percent + massFlow + lowBLnor + upBLnor + chord + bladeAngle
- Test MSE: 37.7
- R-squared: 0.996
- k: 3 - 28
- i: 2 - 30

Data very near hub and tip are ignored



Streamwise velocity

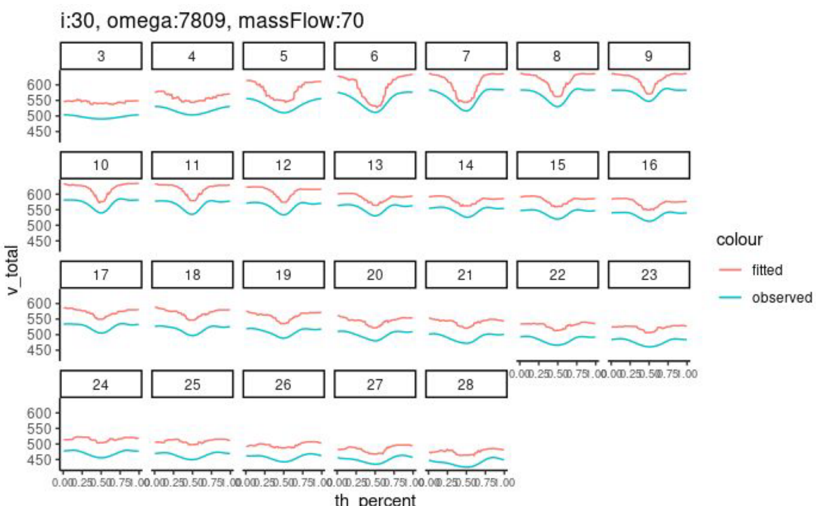


ML method I

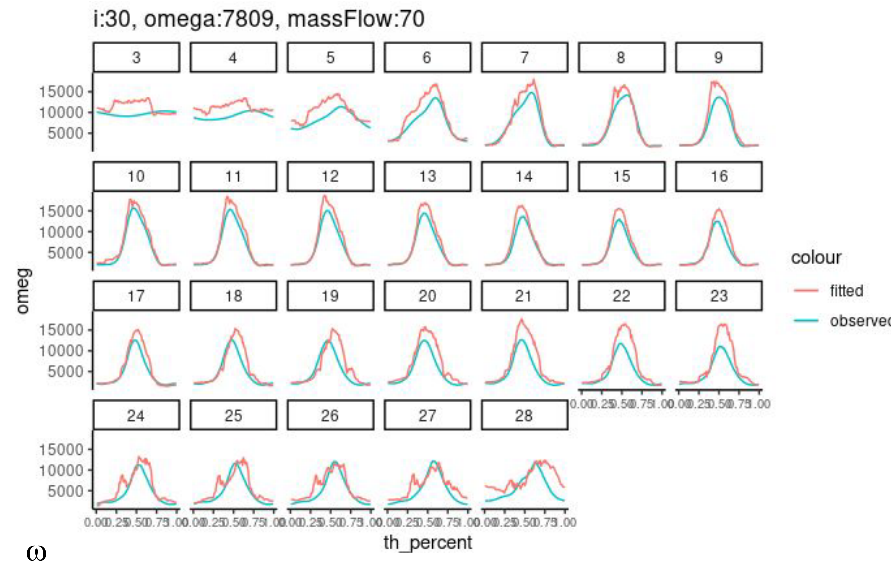
Example: streamwise velocity, XGBOOST, some chosen at random from all wake location points

When leave out some entire mass flow cases

Streamwise velocity shape is fine, magnitude is not so good

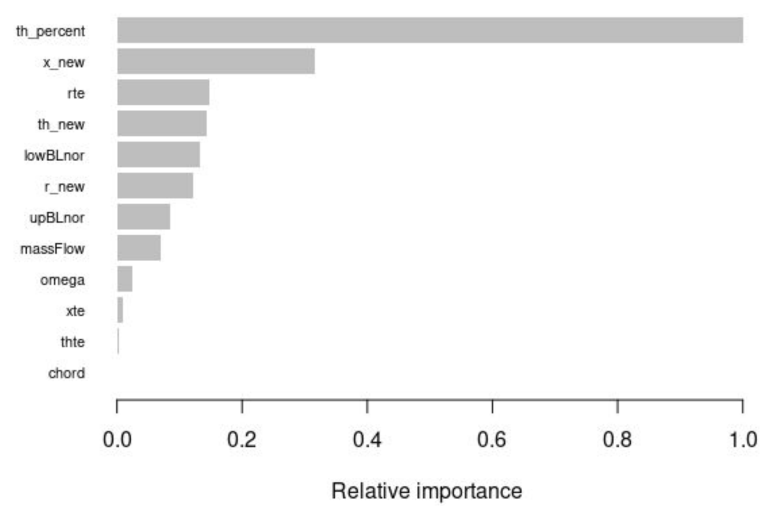


Streamwise velocity



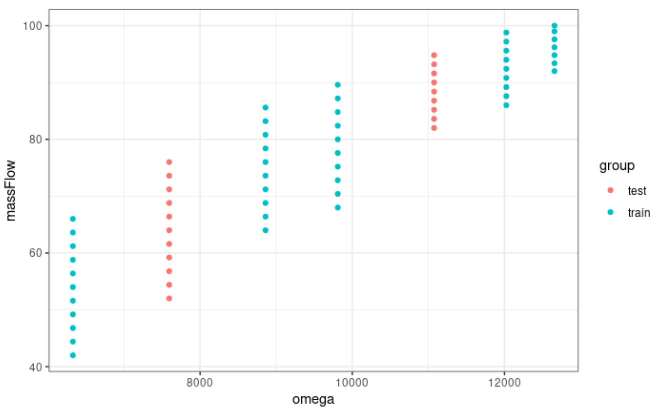
ω

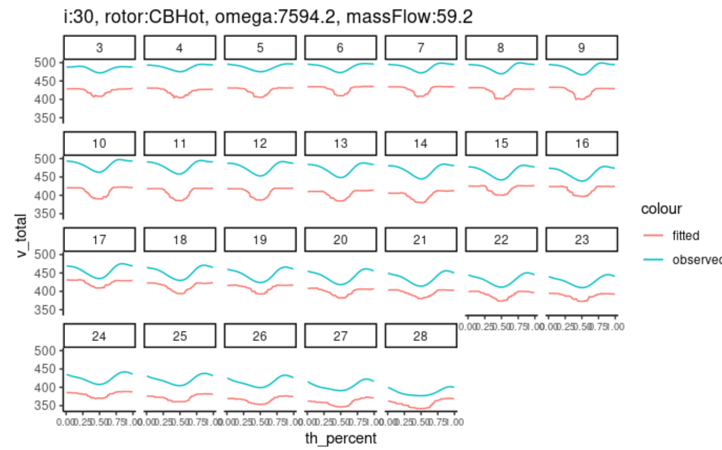
Turbulence dissipation parameter is fine (mass flow not an important parameter!)



ML method I

Example: leave out entire rotor speeds and then try to predict

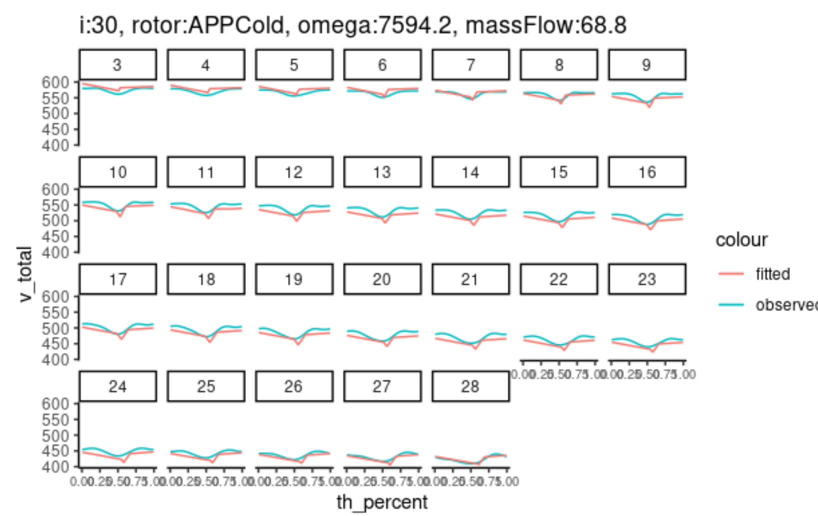




Streamwise velocity (XGBOOST)

Decision tree (XGBOOST) leads to “nearest neighbor” type predictions – shape ok, magnitude off

DNN approach leads to good mean values on a passage but wake shapes are off



Streamwise velocity (DNN)

Note :

Impact on low-order calculations ….

Wake shapes (passage profile) needed for tonal noise

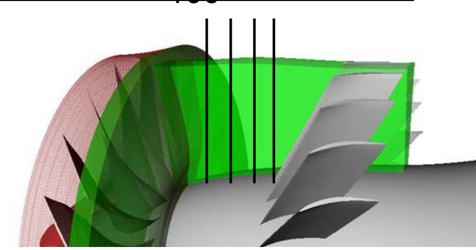
Average value on passage needed for broadband noise
DNN works fine

Machine learning method II

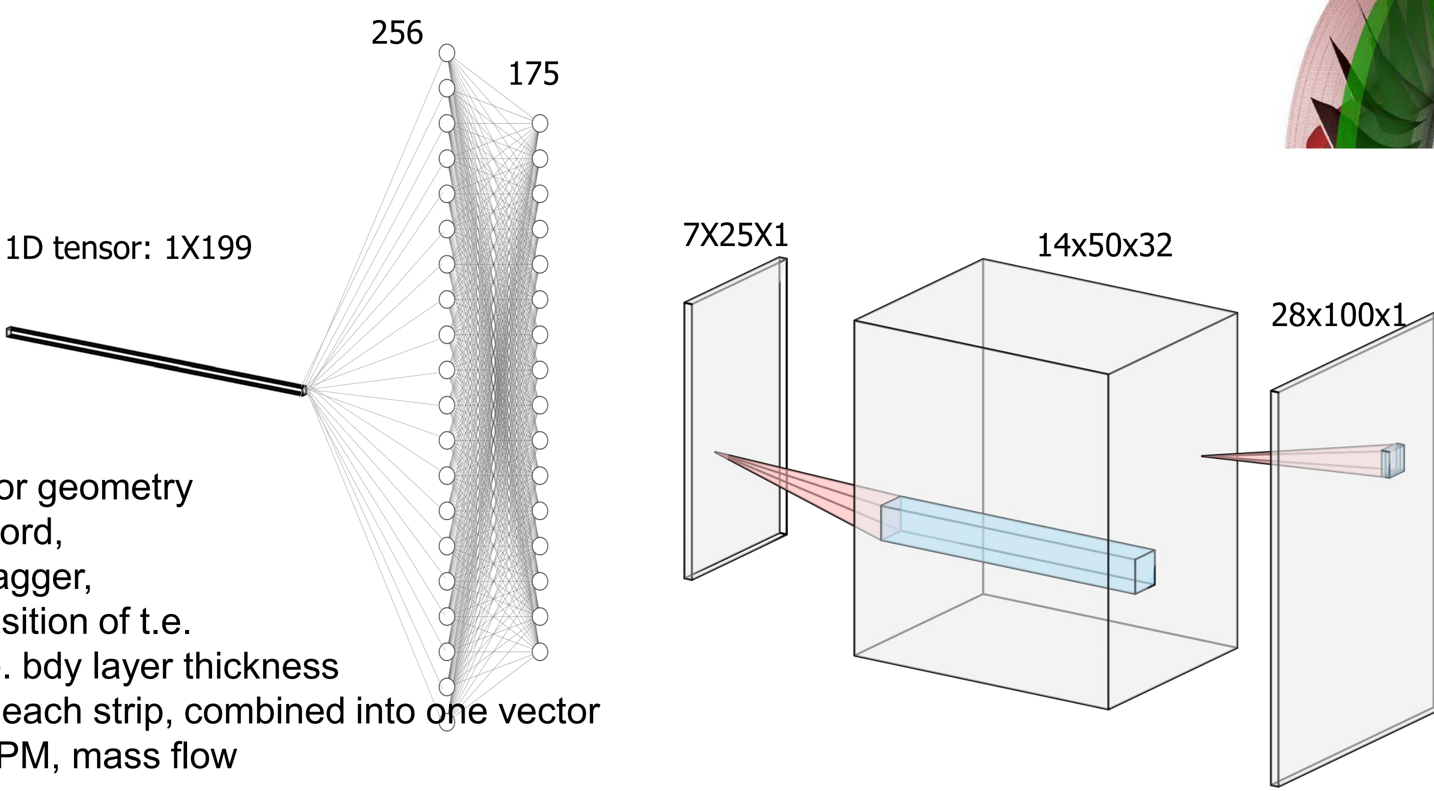
Method 2: multi output

Use all rotor information as one input (no radial slicing)

Learn axial cut "image" as one output



ML: Decoder part of Convolution Neural Network



Rotor geometry
- chord,
- stagger,
- position of t.e.
- t.e. bdy layer thickness

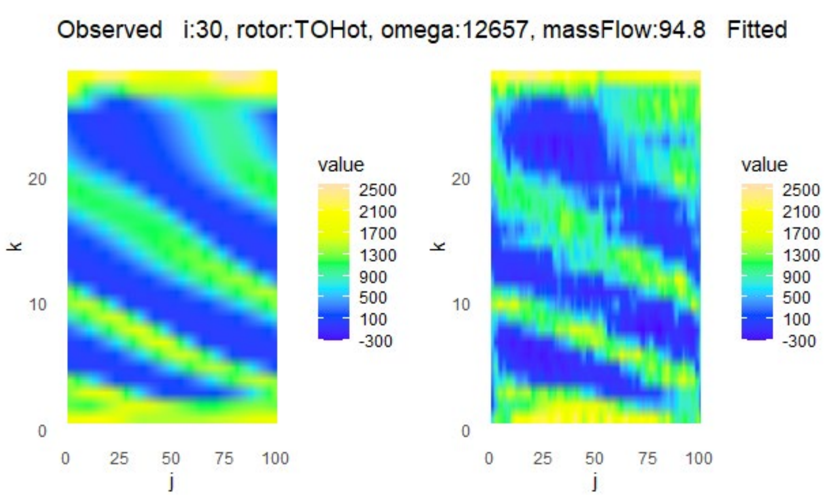
For each strip, combined into one vector
+ RPM, mass flow

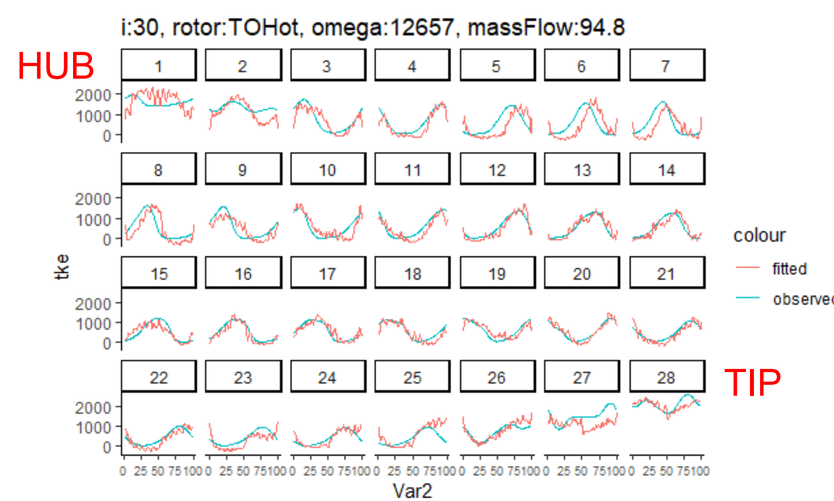
ML method II

Example: CNN, TKE, random selection of axial slices to use for training and testing

- Input: 199
  28 * (r_te, th_te, x_te, lowBLnor, upBLNor, chord, bladeAngle) + omega + massFlow + x
- k: 2 - 29
- i: 1 - 30

} Used 80% of axial slices for training





Must determine reason for jitter
Will explore further options for numbers of layers in CNN etc.

Final ML comment

Historical empirical wake evolution fittings utilized rotor force

In our inputs, we have utilized boundary layer trailing edge thickness and will also use rotor force in the future

Only way to know these parameters currently is to run a simulation, which defeats our purpose

We have efforts ongoing to :

- learn the wake without these parameters as input
- learn these inputs as a first step so they can be used in the wake ML

Summary and future work

Wake parameter surrogate model

Have developed viable single output method :

At this moment would suggest combination of DNN and XGBOOST to fully describe wake

Have demonstrated potential for CNN for multi output

Allows clearer use of rotor case as 1 input and forces “physical” connection of output values

Must fully develop and test

Rotor force data, inflow and outflow angles etc. have not been used as input yet

Both methods will be tested using larger set of rotor input parameters

Test ability to learn rotor force and rotor trailing edge boundary layer thickness

Must increase database, include larger differences in geometry and test ML predictions

Noise prediction (focus on low-order FEGV response)

Full scale test data (CLEEN I) being curated for use in validation study

Year 2 effort includes expansion of low-order capability: nonisotropic turbulence, circumferential asymmetry