# ASCENT Project 075

# Improved engine fan broadband noise prediction capabilities

**Boston University (BU) & Raytheon Technologies Research Center (RTRC)**

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Cost Share Partners: BU, RTRC, Aeroacoustics Research Consortium (AARC)

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## 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.

## 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.

- Continue to test the current LO exit guide vane response method's ability to predict the broadband noise.

## Major Accomplishments (to date):

- Data set : 4 geoms (268 cases); new geoms built
- ML methods for mean flow wake, TKE, $\omega$
  - SDT related geometries
  - Single input tested but probably not main method of interest
  - Multi output ML : CNN for each parameter completed
- Acoustic prediction for all 268 cases & vane location

## Future Work / Schedule: (Spring/Summer)

- ML
  - New geometries -> complete larger data set
  - Additional input parameters (tests); learn BL and forces maybe
  - CNN for mean values : axial - radial view
- Acoustics
  - Full scale prediction (pylon, propagation to field)
  - Tip clearance and inflow asymmetry modeling

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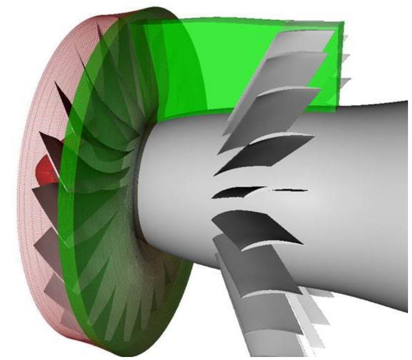
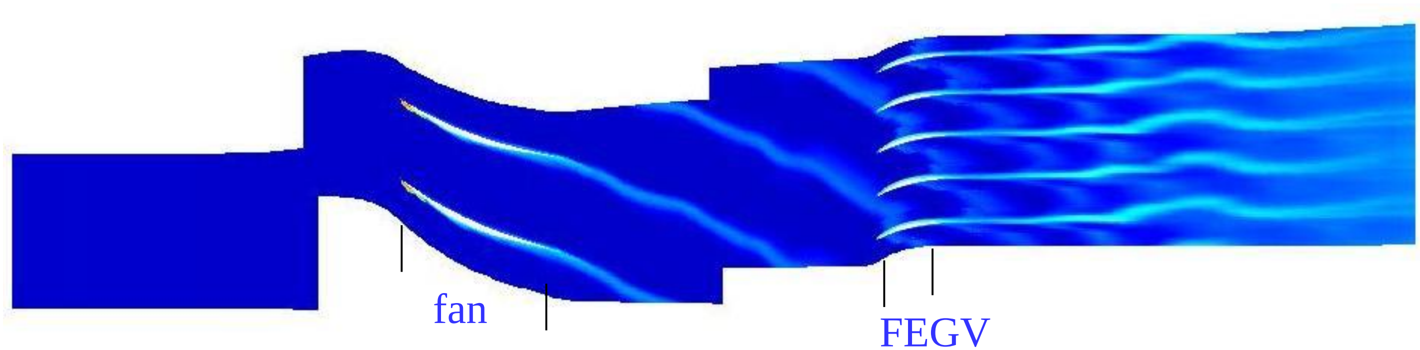
# Fan broadband noise background

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

(This also produces the tonal noise)

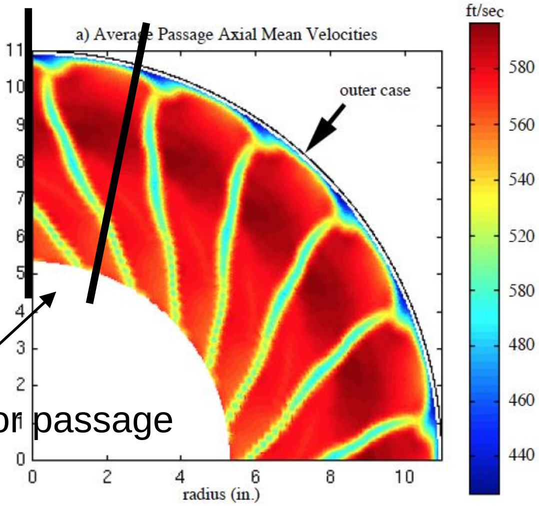





- Low-order method computes the sound by just simulating the FEGV and represents the FEGV in a simplified fasion
- The FEGV inflow is needed

# Low-order FEGV noise calc

## Flow input needed




One rotor passage

Turbulent length scale

$$L_s = \overline{U_s}\int_0^\infty \frac{\overline{u'_s(\tau)u'_s(\tau+t)}}{u_s'^2}\,dt$$

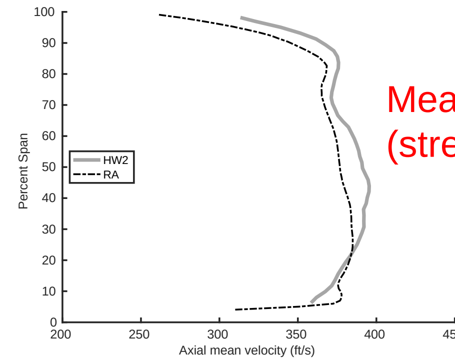
$$= 0.43\frac{\sqrt{K}}{C_\mu \omega_T}$$

RANS method (Pope)

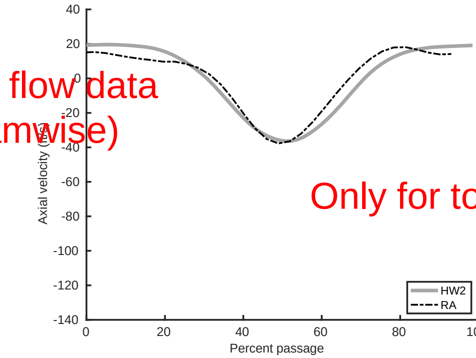
Need K and w

Getting inflow from CFD or experiment renders the entire prediction NOT low order

Hub to tip: overall mean



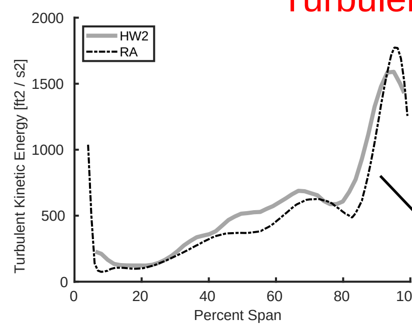

Ave passage near mid

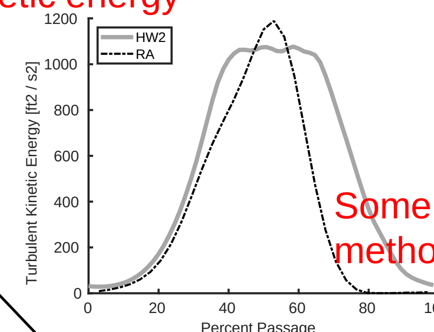



Mean flow data (streamwise)

Only for tonal

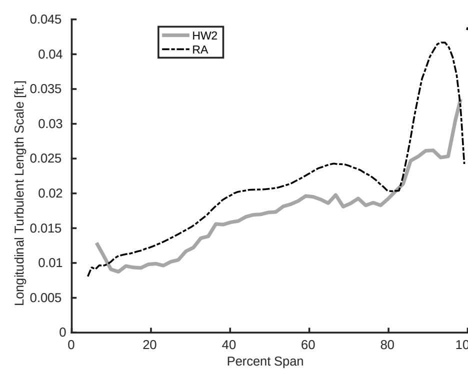
Turbulent kinetic energy




Some LO methods

Turbulent length scale




Liepmann turbulence spectrum

$$E_{3d} = \frac{8u'^2 L_s (kL_s)^4}{\pi(1+(kL_s)^2)^3}$$

Wave number

# Our project

**Main part:**

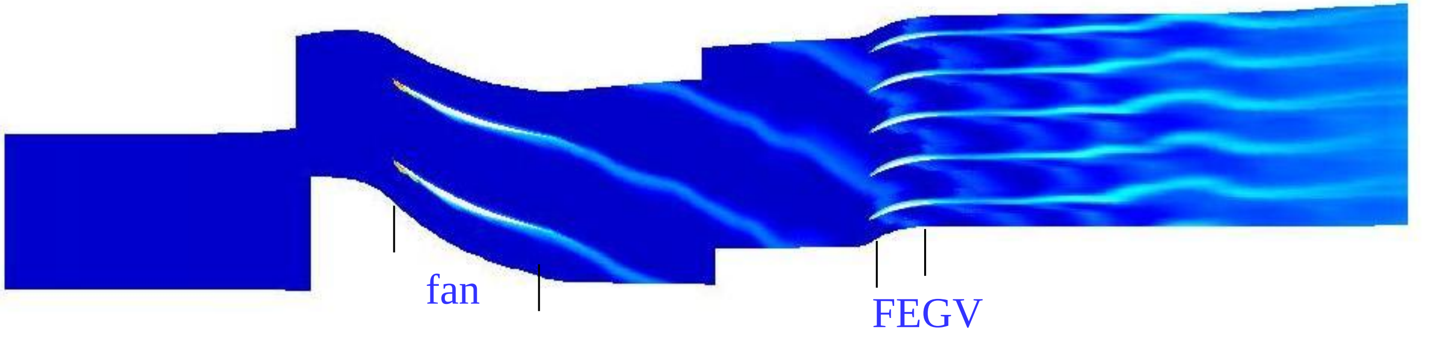
Create a surrogate model for the rotor wake flow (eliminating need for computation or experiment in order to define input for the low-order FEGV calculation)

Use machine learning (ML)

End goal: A ML based surrogate model that provides the mean flow, turbulence intensity, and length scale just upstream of the FEGV given the following inputs: fan geometry, RPM, mass flow, duct geometry and perhaps some other information

**Secondary part:**

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



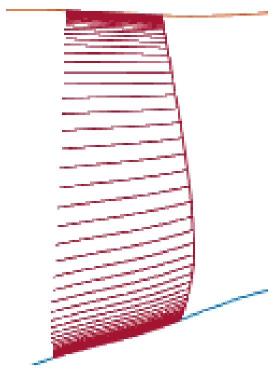
# Machine learning

We have considered 2 basic methods

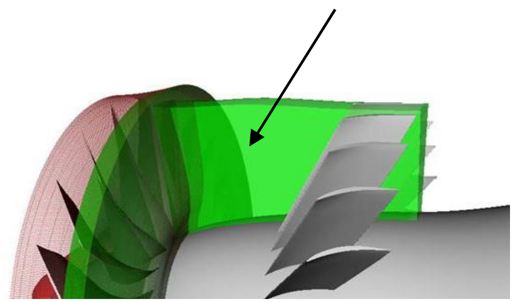
**single output & multi output**

The goal of both :

Define rotor geometry on %radial strips:
- chord,
- stagger,
- position of t.e.
- t.e. bdy layer thickness
- inflow/outflow angle
- force vector



State RPM, mass flow

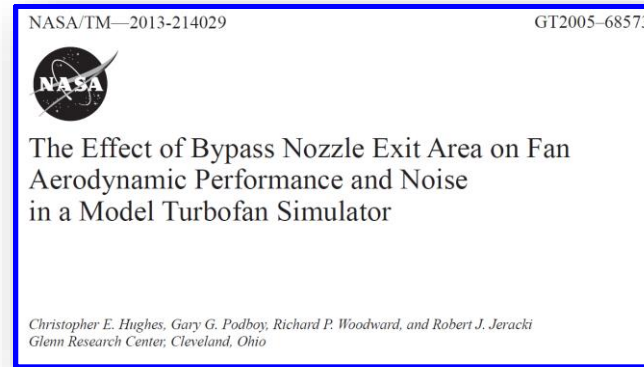


Provide flow values on portion of NxMxP grid in the gap region
- Streamwise velocity magnitude
    - Axial, circumferential, radial
- TKE (k)
- Turbulent dissipation ($\varepsilon$ or $\omega$)

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

# Database for the ML fan

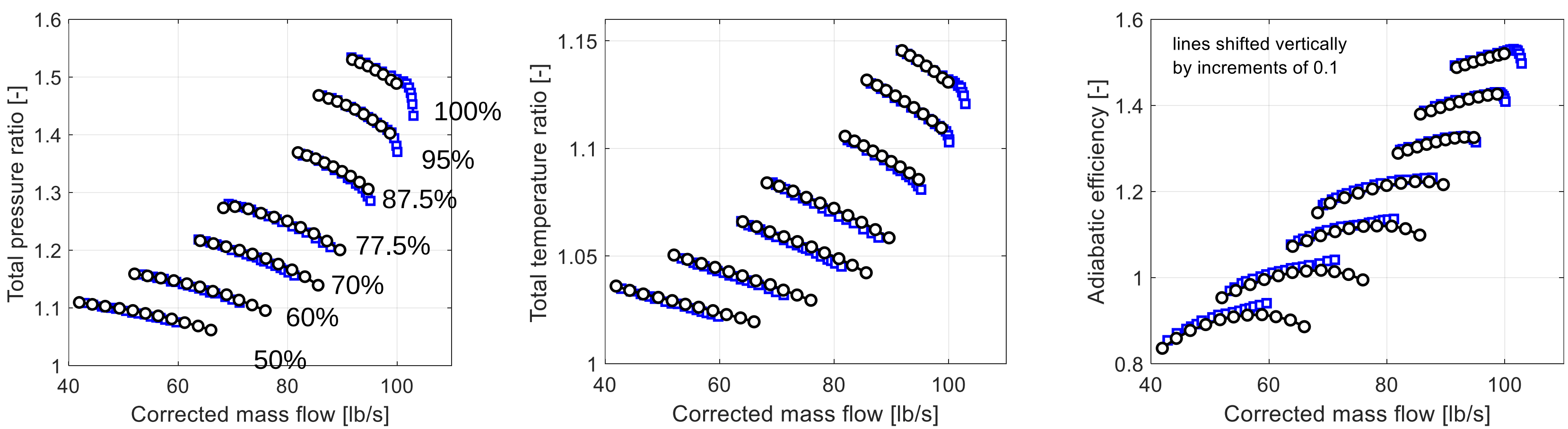
- Use RANS (k-ω), rotor alone simulations in rotor frame
- Geometries : based on NASA SDT
  - CAD (cold), 7808 RPM (hot), 11607 RPM (hot), 12657 RPM (hot)
- 7 RPM : 50%, 60%, 70%, 77.5%, 87.5%, 95%, 100%
- 7-10 mass flow rates at each RPM
- Total of 268 cases


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*

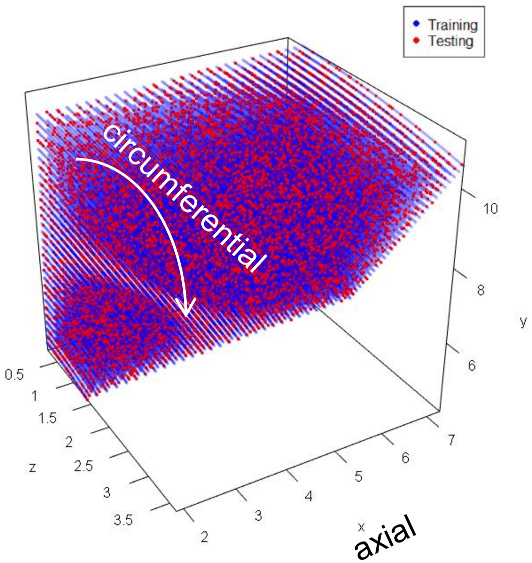
Example: SDT cold. EXP data (digitized from NASA TM, fan alone performance)



# Machine learning

We have considered 2 basic methods so far

## Method 1: single output




Used splines, MARS, XGBOOST with decision tree, DNN

Tested necessary size of N x M x P (3D grid in gap)
Tested method for selecting which data to use for training/testing
(i) Random selection out of N, M, P (what %: 80% train, 20% test,..)
(ii) Leave out entire N (axial locations), leave out mass flow case, ...

Can get very good predictions of test cases when rotor geometries are similar

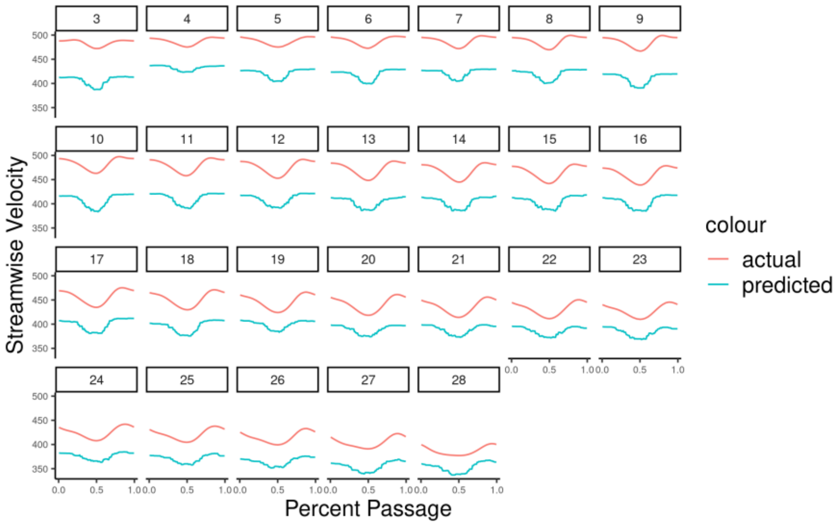
Noted that for mean flow average passage, overall mean had to be subtracted and learned separately

# ML method I

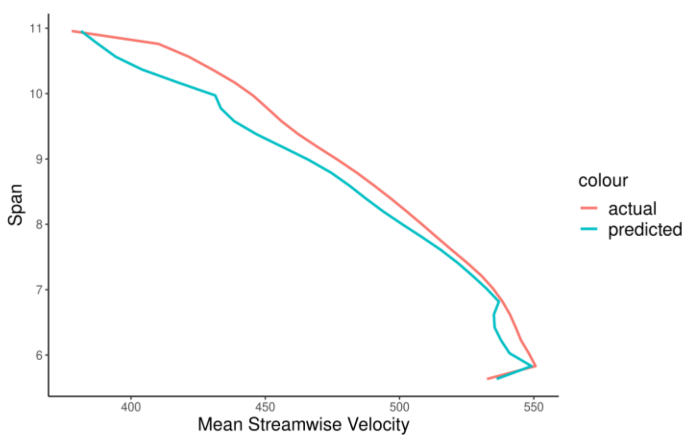
Example: streamwise velocity, XGBOOST

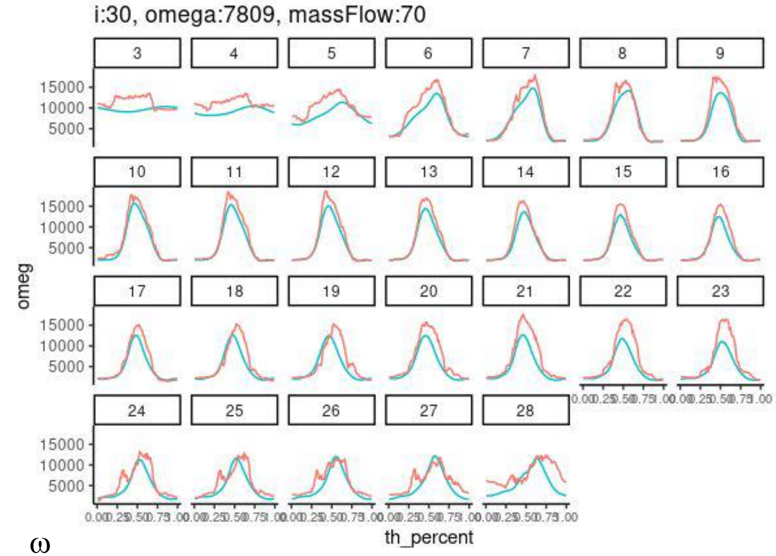
When leave out some entire mass flow cases

Streamwise velocity shape is fine, magnitude is not so good

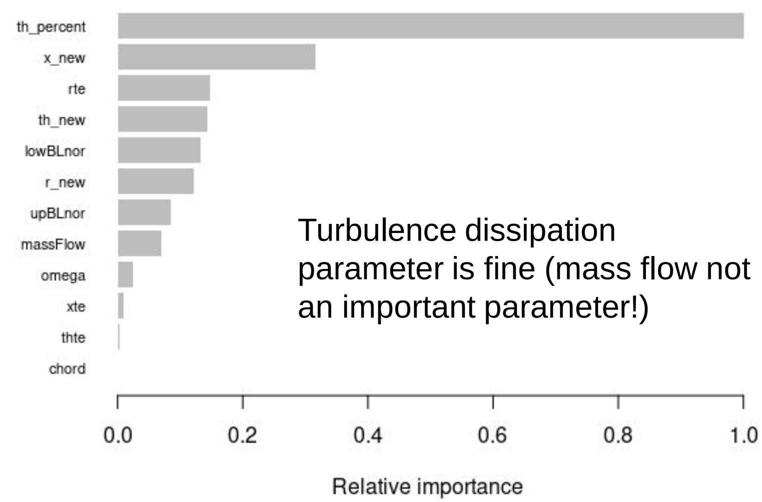



Streamwise velocity




ω



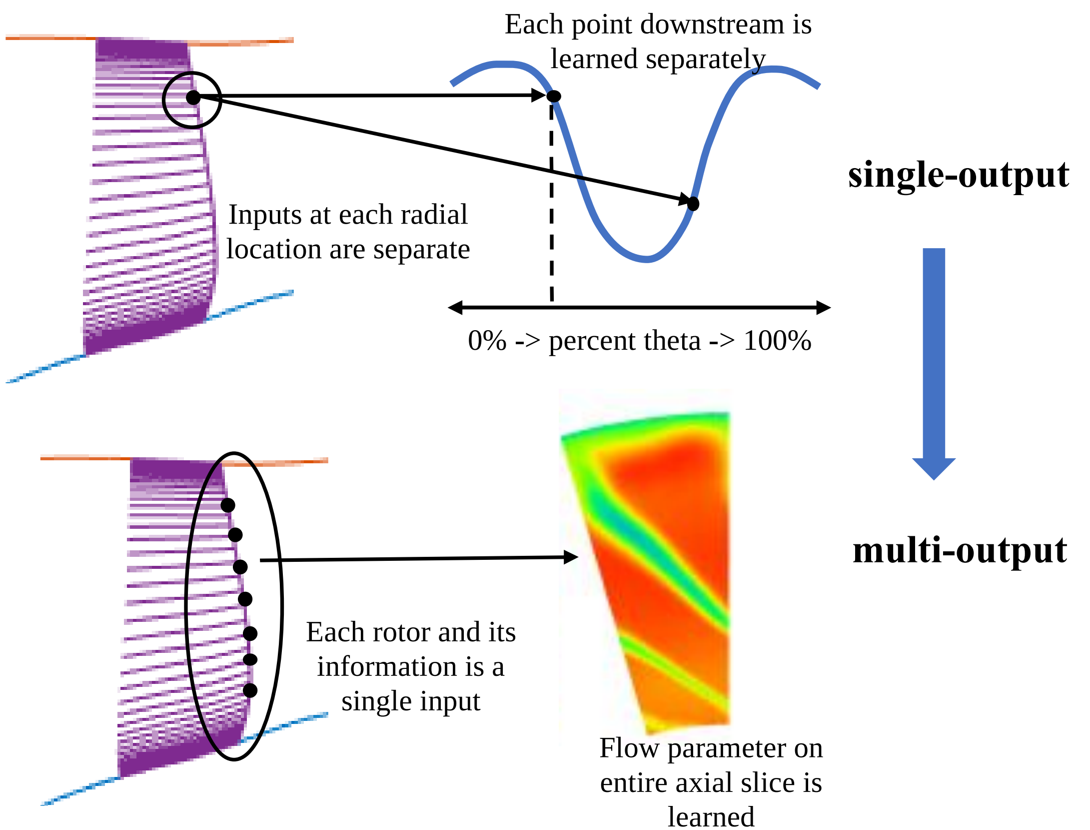

Turbulence dissipation parameter is fine (mass flow not an important parameter!)

# 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



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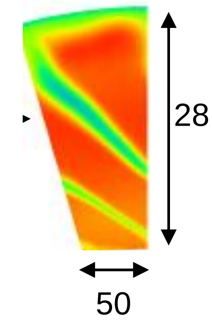
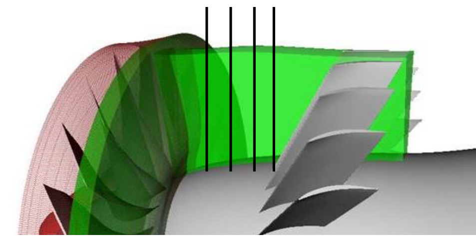
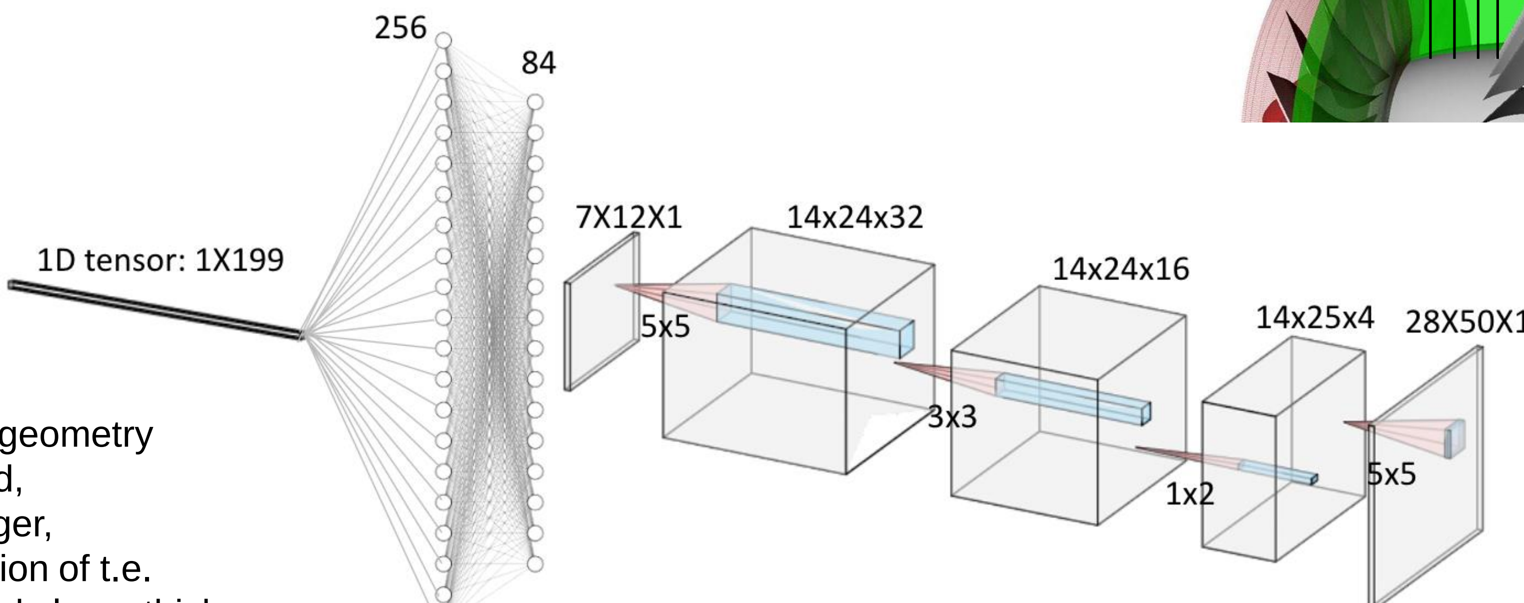



ML: Decoder part of Convolution Neural Network






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

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

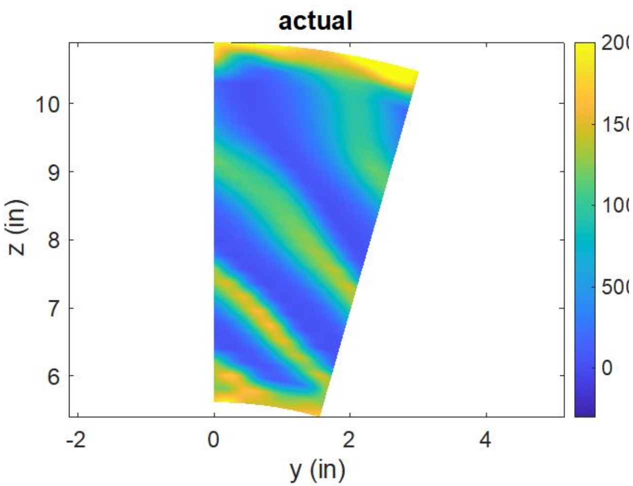
# ML method II

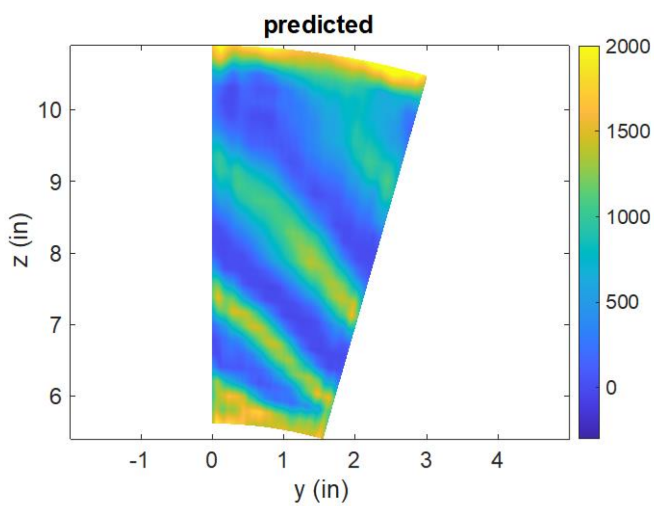
CNN, **TKE**, random selection of axial slices to use for training and testing

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

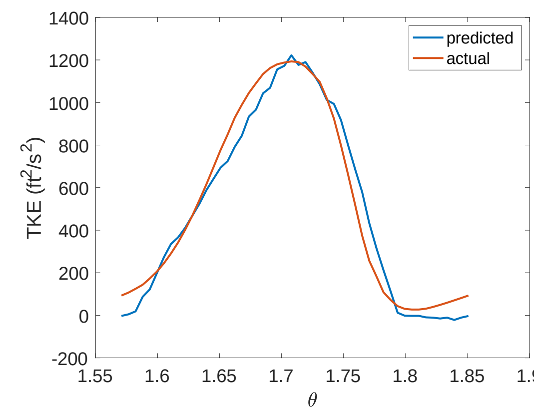
Used 80% of axial slices for training

TOHot geom, 12657 rpm, 94.8 lbm/s, i = 30




Mid span slice



# ML method II

CNN, **TKE**

CNN architecture

| Structure | Numbers of feature maps | Size of feature map | Size of kernel | Stride |
|---|---|---|---|---|
| Fully connected layer-1 | 256 | 1×1 | / | / |
| Fully connected layer-2 | 84 | 1×1 | / | / |
| Transposed 2D convolution layer-1 | 32 | 7×12 | 6×6 | 1×1 |
| Transposed 2D convolution layer-2 | 64 | 7×12 | 3×3 | 1×1 |
| Transposed 2D convolution layer-3 | 64 | 14×24 | 4×4 | 2×2 |
| Transposed 2D convolution layer-4 | 16 | 14×24 | 5×5 | 1×1 |
| Transposed 2D convolution layer-5 | 32 | 14×24 | 3×3 | 1×1 |
| Transposed 2D convolution layer-6 | 32 | 14×25 | 1×2 | 1×1 |
| Transposed 2D convolution layer-7 | 2 | 28×50 | 3×3 | 2×2 |
| Transposed 2D convolution layer-8 | 1 | 28×50 | 3×3 | 1×1 |

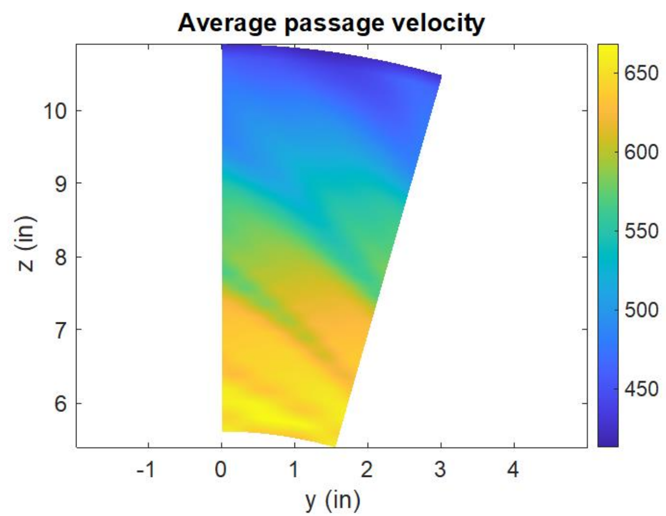
CNN model parameters

| Parameter | Value |
|---|---|
| Activation function at hidden layer | LReLU($\alpha = 0.05$) |
| Activation function at output layer | Linear |
| Optimizer | Adam |
| Learning rate | 0.001 |
| Objective function | Mean squared error |
| Metrics | Mean absolute error |
| Number of epochs | 325 |
| Mini batch size | 128 |

# ML method II

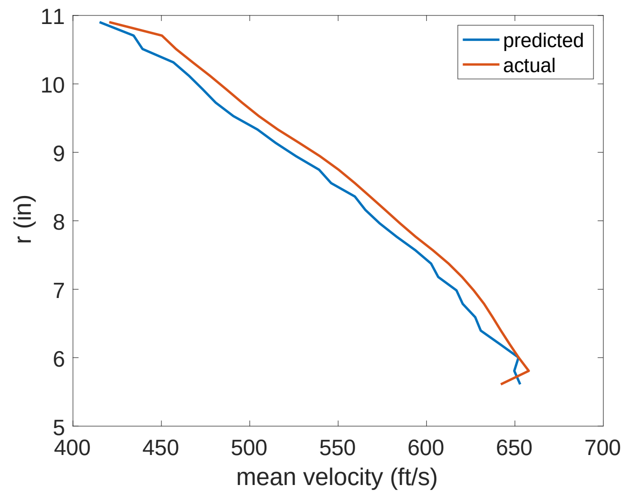
CNN, **Mean flow**, random selection of axial slices to use for training and testing

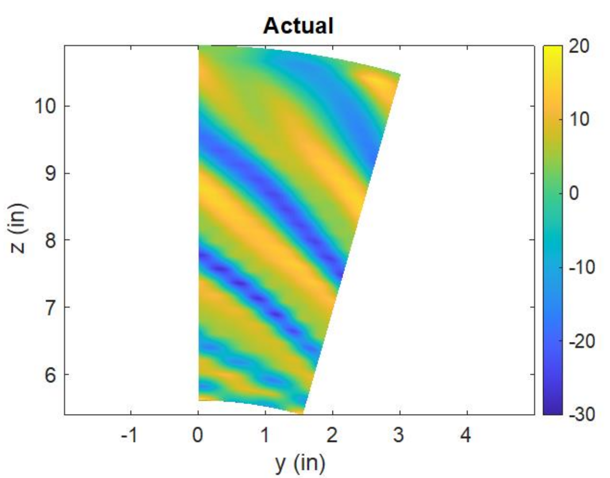
CBHot geom, 7594 rpm, 76 lbs/s, i = 30

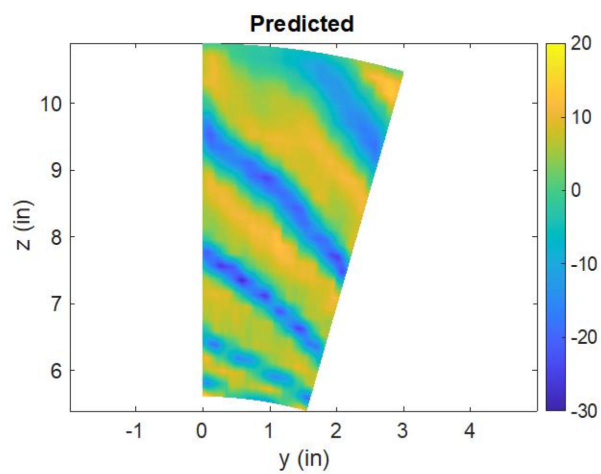



Wake deficit hidden under mean. ML doesn't work well.

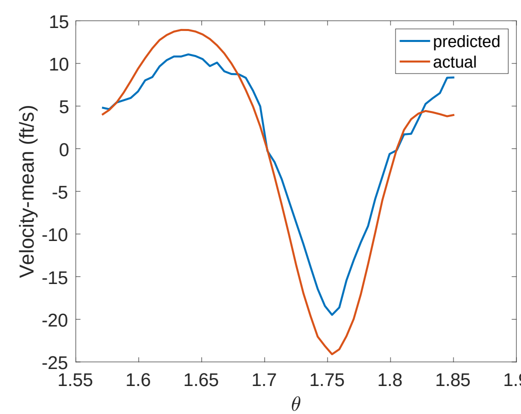
Subtract off overall mean




Mid span slice



# Final ML comment

Multi output method provides correlation in circumferential and radial directions which is desirable

Method working well

Rotor geometries all very similar

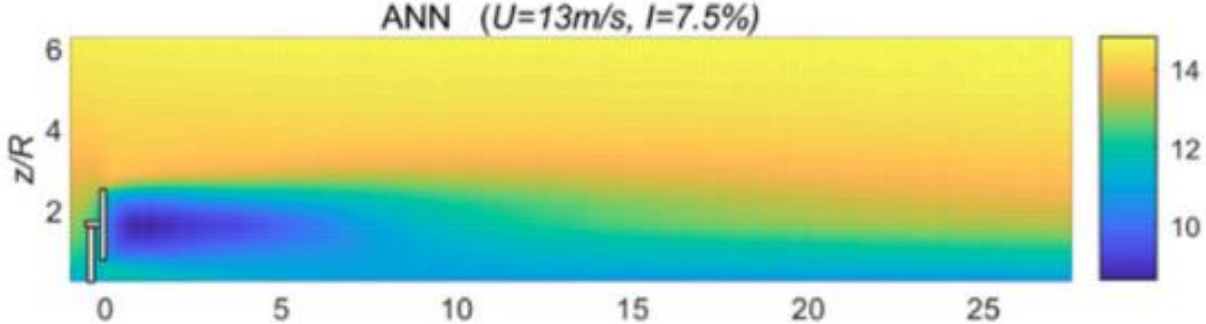
Each variable requires a different CNN architecture (overall mean, wake deficit, TKE, $\omega$)

Broadband only requires overall average values.  Leads to interest in considering different flow view.

In wind turbine ML they consider correlation of axial and radial

circumferential not required (averaged)

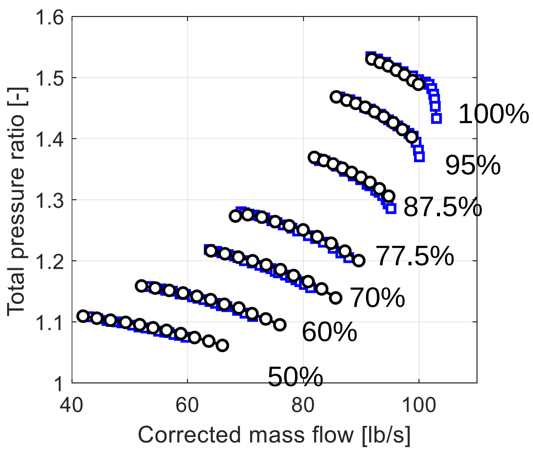
Will try this approach in future : must deal with annular shape difference in axial direction

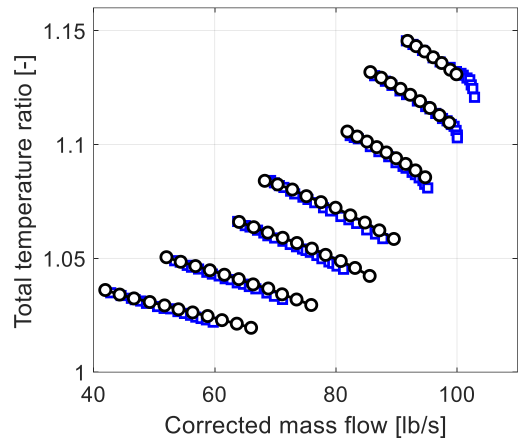


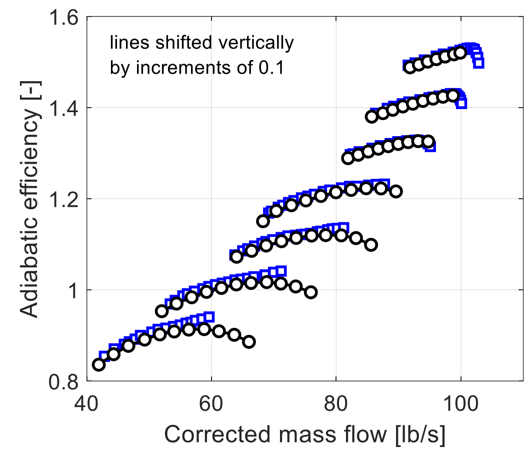

Z. Ti et.al., Wake modeling of wind turbines using machine learning. Applied Energy. 257:1-17, 2020

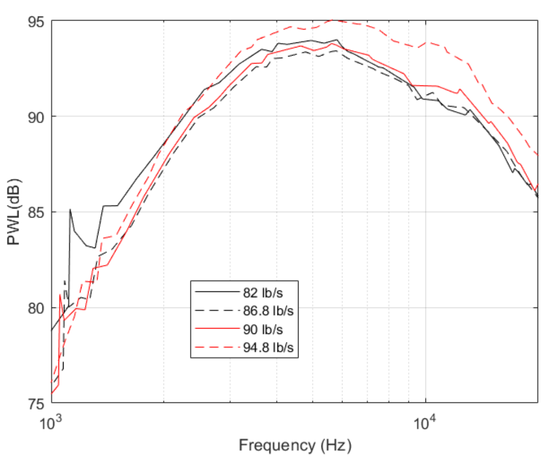
# Broadband fan acoustics

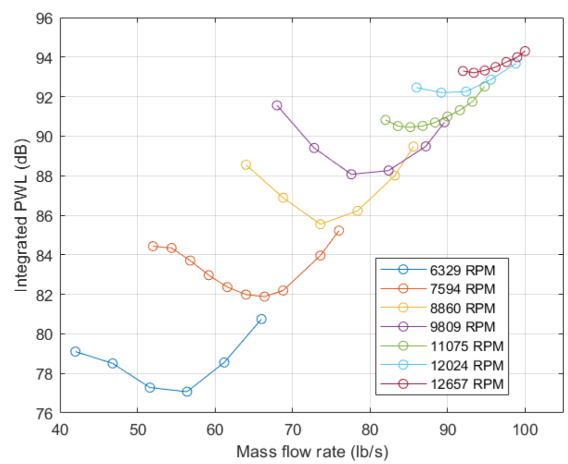
268 cases run : Use them to explore acoustics




Integrated acoustic spectra (600Hz – 20kHz)

Trend does not follow total pressure ratio or efficiency.

Noise increases with increasing RPM

Optimal mass flow at given RPM

# Broadband fan acoustics

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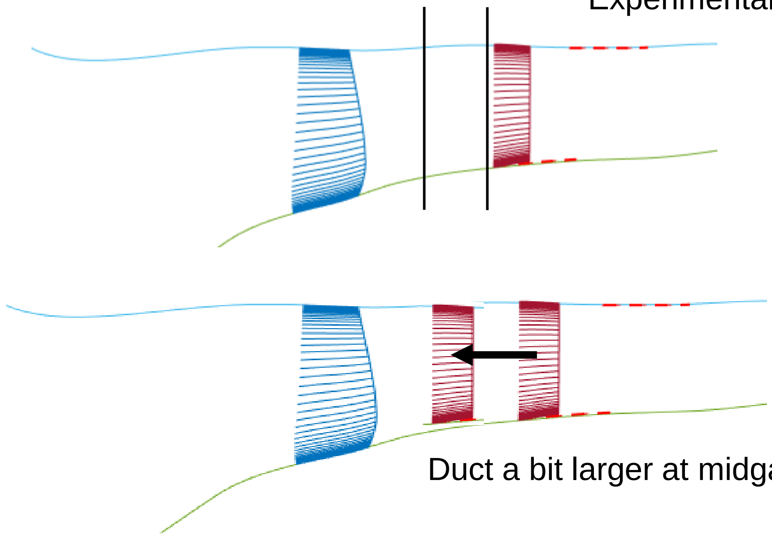
AVIATION SUSTAINABILITY CENTER

Placement of vane in fan-stage

Experimental data taken midgap and just upstream of vane



Duct a bit larger at midgap

What if vane is moved to the midgap location

Tonal noise : goes up with decreased gap distance

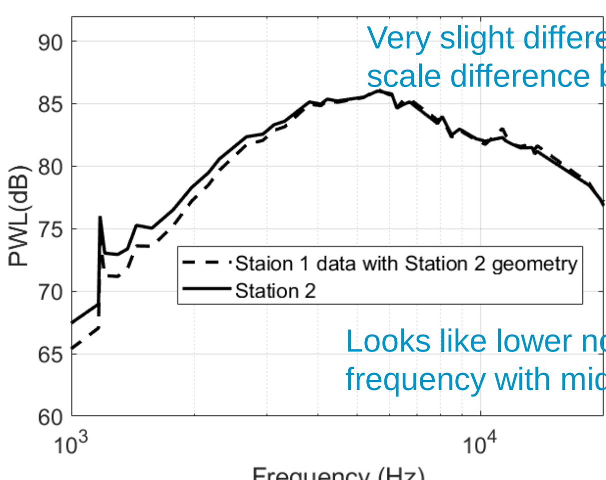
Tones can be managed

Broadband : little change! influenced by 2 things

Vane inflow turbulence

Duct geometry

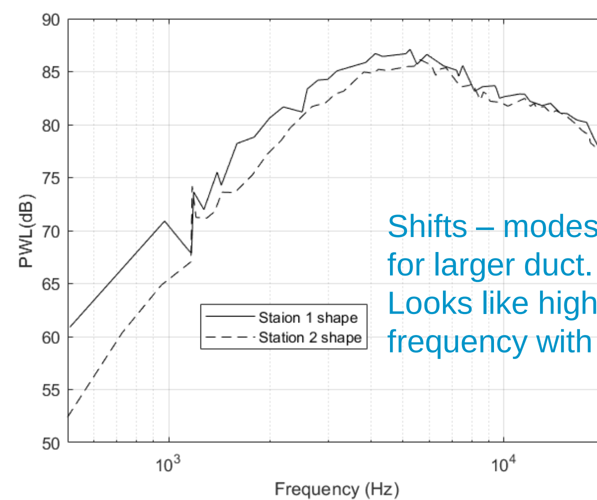
Influence of inflow
(map values onto original vane/duct size)




Very slight different due to length scale difference between two locations

Looks like lower noise at low frequency with mid-gap inflow

Influence of duct size
(use same inflow on two different ducts)




Shifts – modes cut on earlier for larger duct.
Looks like higher noise at low frequency with mid-gap geom

# Broadband fan acoustics

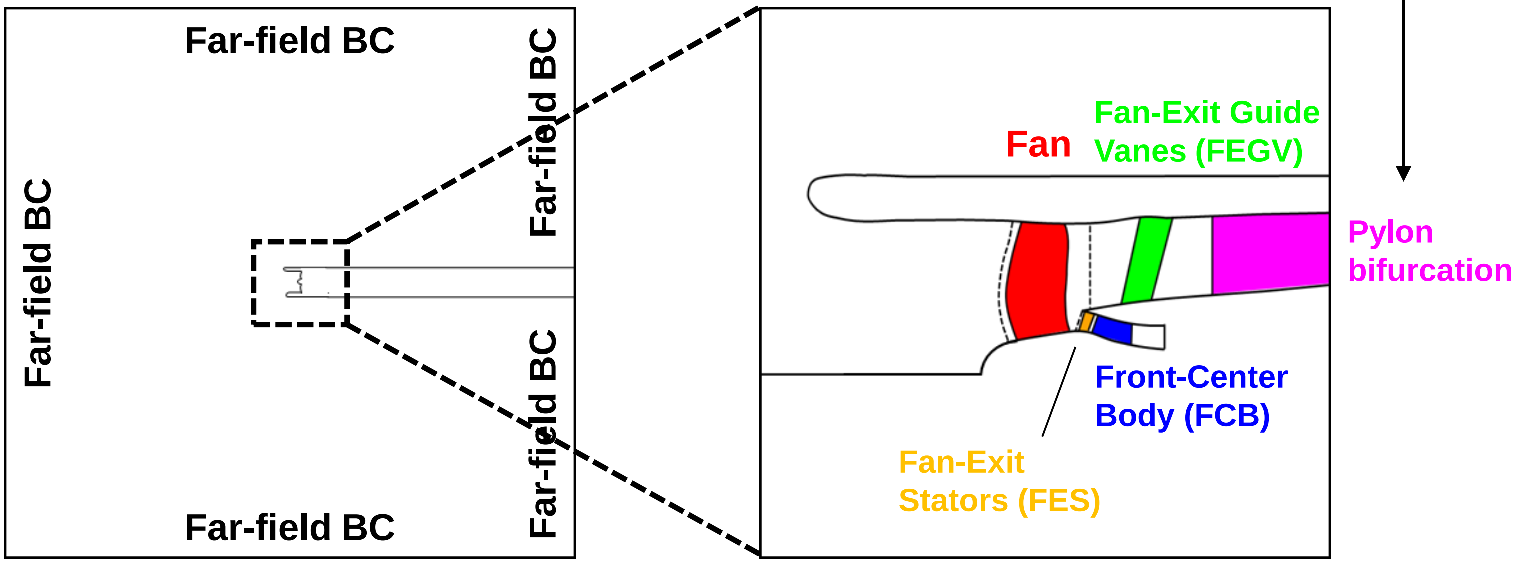
Testing prediction of full-scale:  FAA CLEEN 1

**Available cases:**

- Approach, Cutback, and Sideline power conditions
- Free-stream: M = 0.01 (Ground test conditions)

1) Considering importance of including pylon effect

**Two challenges**



# Broadband fan acoustics

Testing prediction of full-scale:  FAA CLEEN 1

**Test Stand Engine Data**

- Far-field microphones
  - 150ft. arc polar array
  - Acoustic spectra at range of directivity angles

- Source Separated Data
  - Fan Inlet Broadband
  - Fan Aft Broadband
  - Other noise sources

2) Must consider propagation in order to compare with field microphones

# Summary and future work

**Wake parameter surrogate model**

All initial findings show promise for this capability – will enable broadband noise as design consideration

Add further inputs to the ML : rotor force data (compare to current predictions that do not use this input)
Determine difference in ability to learn wake with and without boundary layer thickness as input
If ML needs these parameters : test ability to learn them

Increase database, include larger differences in geometry and test ML predictions

Use ML to learn overall mean values using axial-radial view (deal with length scale heuristic form)

**Noise prediction (focus on low-order FEGV response)**

Have analyzed influence of mass flow on noise and slight rotor geometry differences

Have begun study of effect of tip clearance

Full scale test data (CLEEN I) being curated for use in validation study
Considering inclusion of downstream pylon effect and propagation to the field mics

Will determine if low-order can be modified to handle asymmetry in inflow to stator caused by nonuniform inflow to the rotor

# Questions ?