ASCENT Project 075

Improved engine fan broadband noise prediction capabilities

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

PI: Sheryl Grace, Jeff Mendoza, Julian Winkler, Craig Reimann

PM: Chris Dorbian

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

Students: Noah Li (PhD), Yifan Zhang (MS), Amaryllis Wiltz (UG)

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 or mid-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 : SDT, new lean, swept
- ML methods for mean flow wake, TKE, length scale
  - Single CNN architecture for all parameters
  - GPU based computations allowing faster analysis
  - New fan lean and swept geometries
  - Averaged quantities learned well
- Acoustic prediction for all 800+ cases

Future Work / Schedule: (Spring/Summer)

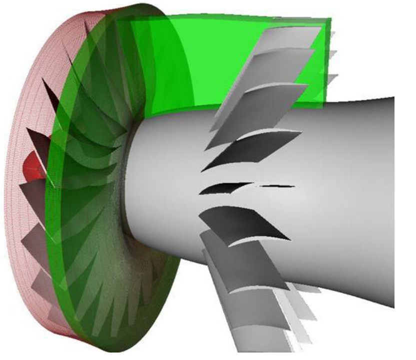
- ML
  - Further new geometries, different number of fan blades
  - Merged all geometries into one data set
  - Update inputs, update method
- Acoustics
  - Full scale prediction – comparison to data
  - Inflow asymmetry modeling
  - Run rig tests at RTRC (sweep, lean)

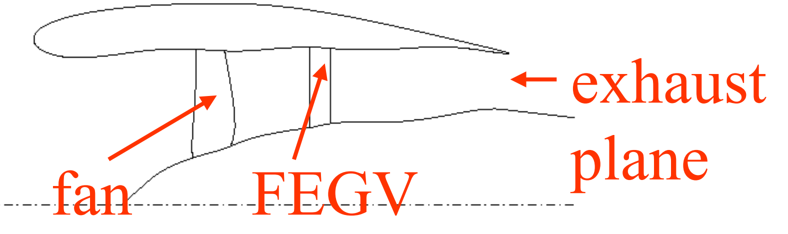
This research was funded by the U.S. Federal Aviation Administration Office of Environment and Energy through ASCENT, the FAA Center of Excellence for Alternative Jet Fuels and the Environment, project 075 through FAA Award Number 13-C-AJFE-BU - amendment 022 under the supervision of Chris Dorbian. Any opinions, findings, conclusions or recommendations expressed in this this material are those of the authors and do not necessarily reflect the views of the FAA.

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 fashion
- The FEGV inflow is needed

Our project

Main goal:

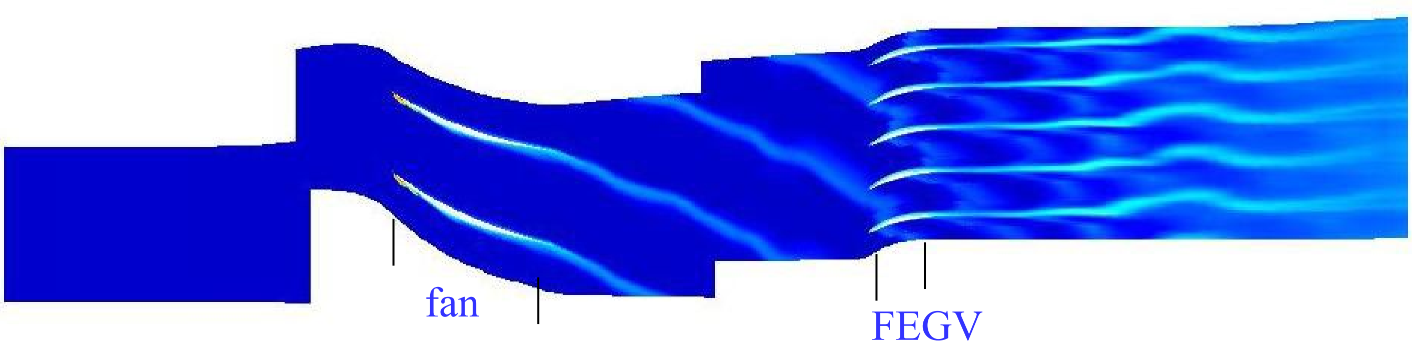
Create a surrogate model for the fan wake flow (eliminating need for computation or experiment in order to define input for the low-order FEGV calculation)

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

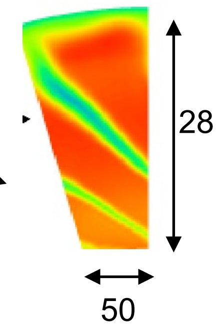
Secondary part:

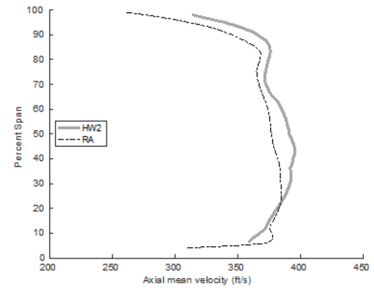
Test and improve the low-order FEGV response method: full scale validation, relaxation of some assumptions



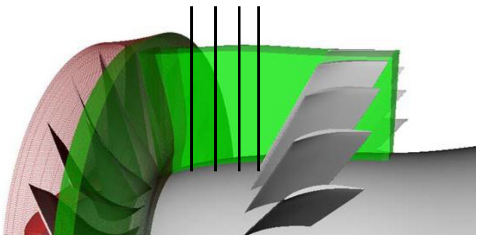
Machine learning for wake flow

Learn axial cut "image" for parameter of interest



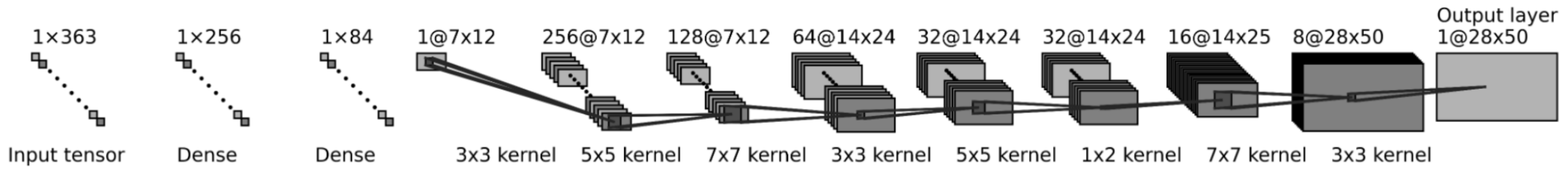


Convolution Neural Network : decoder part
Deep Neural Network



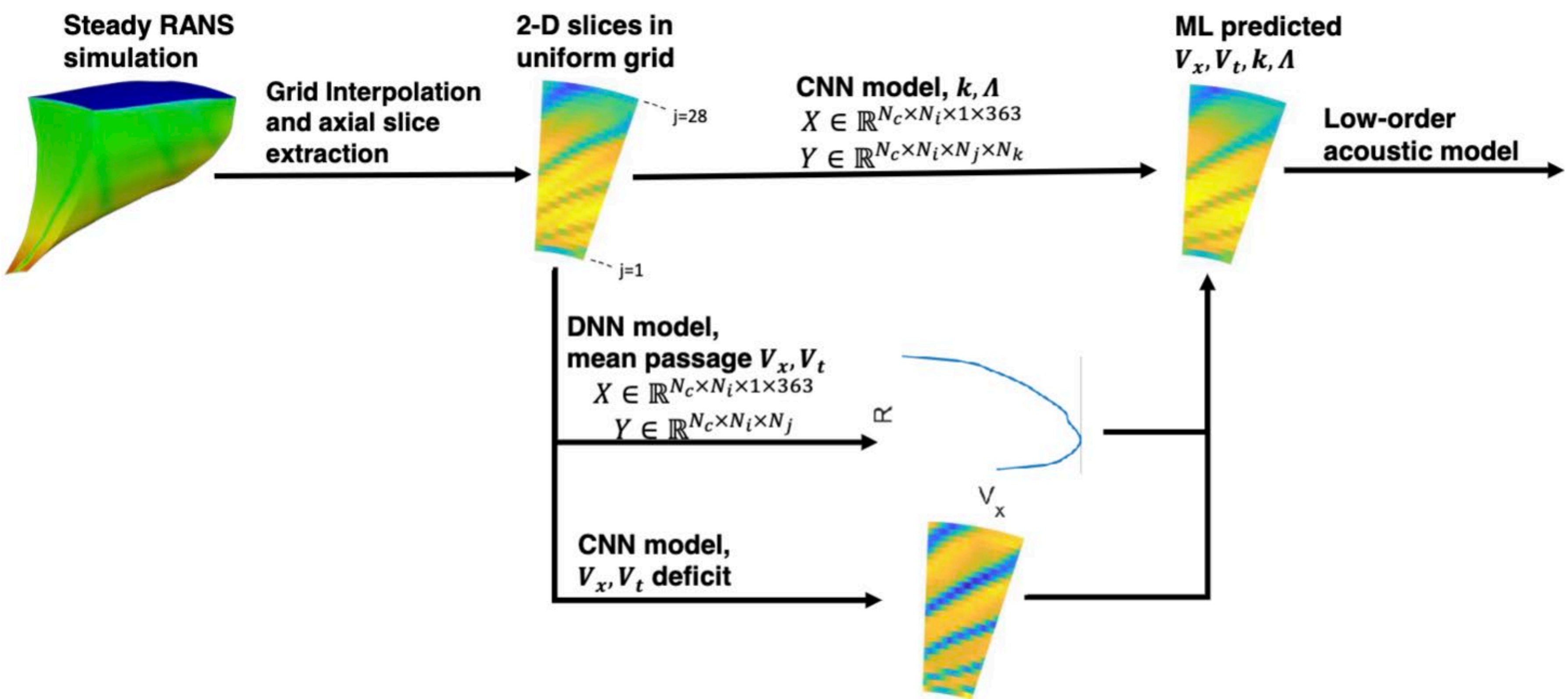
Input
Fan speed
Mass flow into fan
Fan geometry (at diff radial locations)
Few variables from AxStream (at different radial locations)

Training data : either 2d pictures (CNN) or single curve (DNN)
at various axial locations



Machine learning for wake flow

Machine learning for wake flow



Tensorflow – Keras on GPUs with python wrapper for both the DNN and CNN
3.04 million total parameters to learn

ML method

Input name	Size
Rotor speed	1×1
Mass flow rate	1×1
Axial location training slice relative to rotor trailing edge, x_{TE}	1×30
Relative circumferential location of rotor trailing edge, θ_{TE}	1×30
Rotor chord, c	1×30
Stagger angle, χ	1×30
Rotor camber angle, Φ	1×30
Rotor outlet flow angle, α_{out}	1×30
Rotor solidity, σ	1×30
Rotor inlet Mach number, M_{in}	1×1
Rotor outlet Mach number, M_{out}	1×30
Maximum profile thickness/chord ratio, $T_{relative}$	1×30
Maximum thickness of rotor profile, T_{max}	1×30
Outlet metal angle, Φ_{out}	1×30

$x - x_{TE}$

$$\frac{\theta_{TE} - \theta_{min}}{\theta_{max} - \theta_{min}}$$

Size of input: 1x333

ML method

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	256	7×12	3x3	1×1
Transposed 2D convolution layer-2	256	7×12	3x3	1×1
Transposed 2D convolution layer-3	128	7×12	3x3	1×1
Transposed 2D convolution layer-4	64	14×24	5x5	2x2
Transposed 2D convolution layer-5	32	14×24	7x7	1×1
Transposed 2D convolution layer-6	32	14×24	3x3	1×1
Transposed 2D convolution layer-7	16	14×25	1×2	1×1
Transposed 2D convolution layer-8	8	28×50	7x7	2x2
Output layer	1	28×50	5x5	1×1

CNN model parameters

Parameter	Value
Activation function at hidden layer	LeakyReLU
Optimizer	Adam
Learning rate	0.0005 and exponential decay function
Objective function	Mean squared error
Metrics	Mean absolute error
Batch size	256

Learning rate:
0.0005 for Λ,

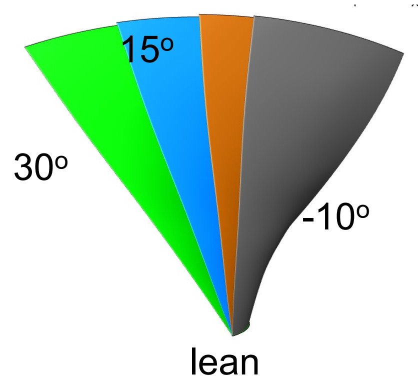
$(Initial\ learning\ rate) \cdot 0.94^{\left(\frac{step}{decay\ step}\right)}$ for v_x, v_t deficit and TKE, where initial learning rate = 0.005 for TKE, and 0.002 for v_x, v_t deficit. Decay step = 200, i.e. learning rate is updated by this function every 200 steps.

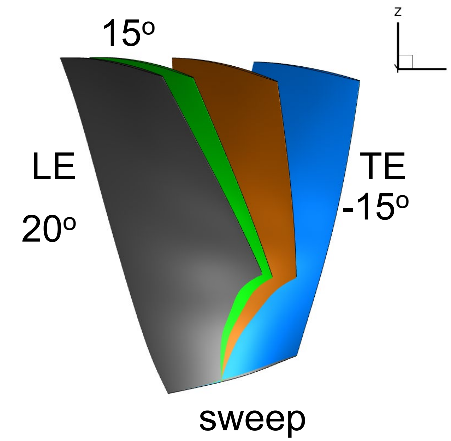
A step is an iteration over a random batch within an epoch, and an epoch is a full cycle throughout the training set.
# of steps = (# of training slice)/(batch size)

Machine learning for wake flow

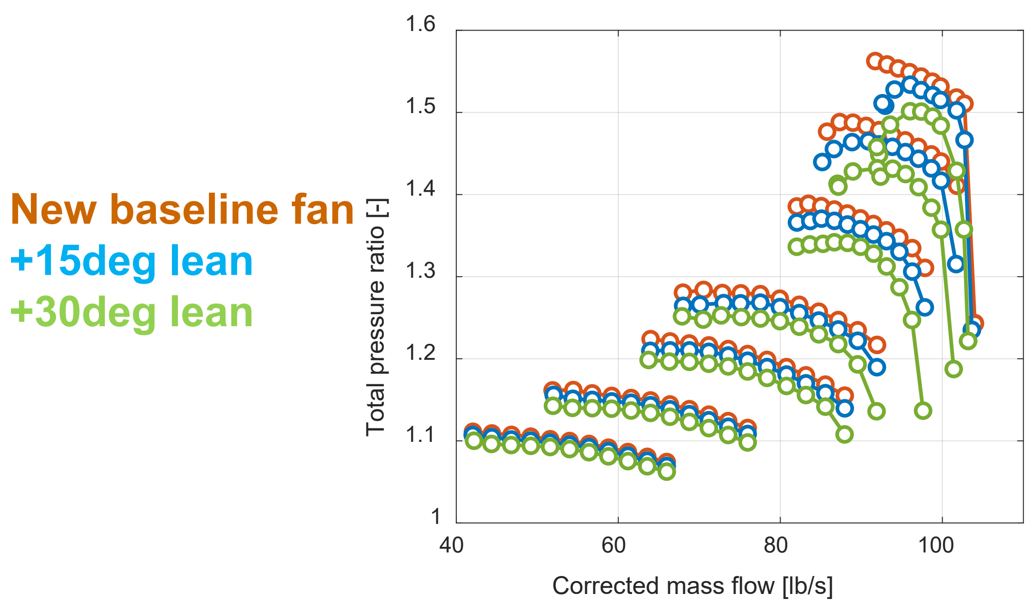
Current database includes

- *SDT fan (rig scale) – 4 geometries that are almost the same*
- *Generic baseline fan*
- *3 leaned fans*
- *3 swept fans*
- *1 lower blade count fans*





At 7 rotation speeds with about 10 mass flow rates each



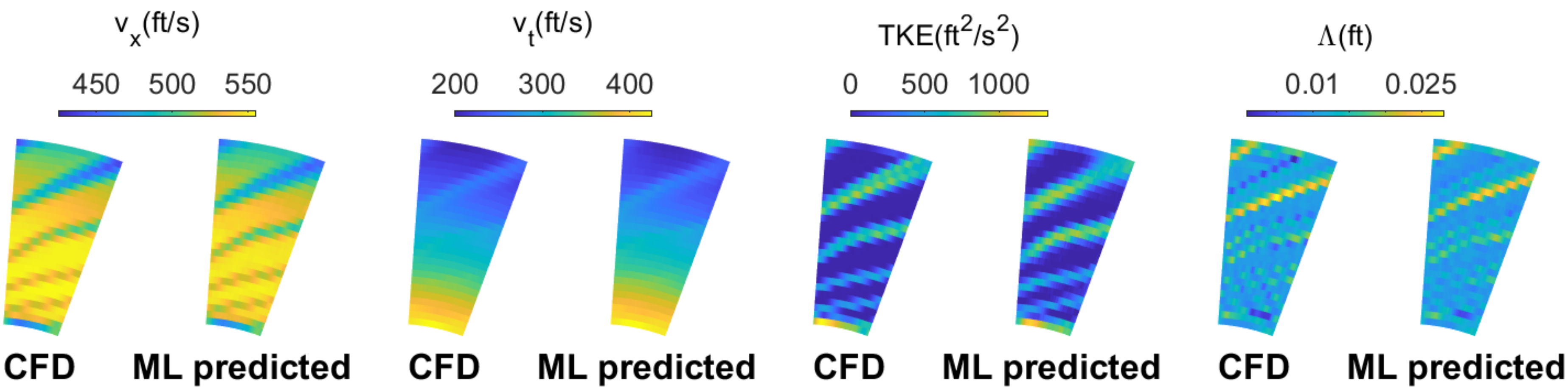
Machine learning for swept wake flow

Database : SDT cutback hot and swept new geometries (no leaned cases)

Leave out 20% of the cases, train and validate with 80%, then test on the 20%

Leave out an entire speed line, train/validate and then test on case left out

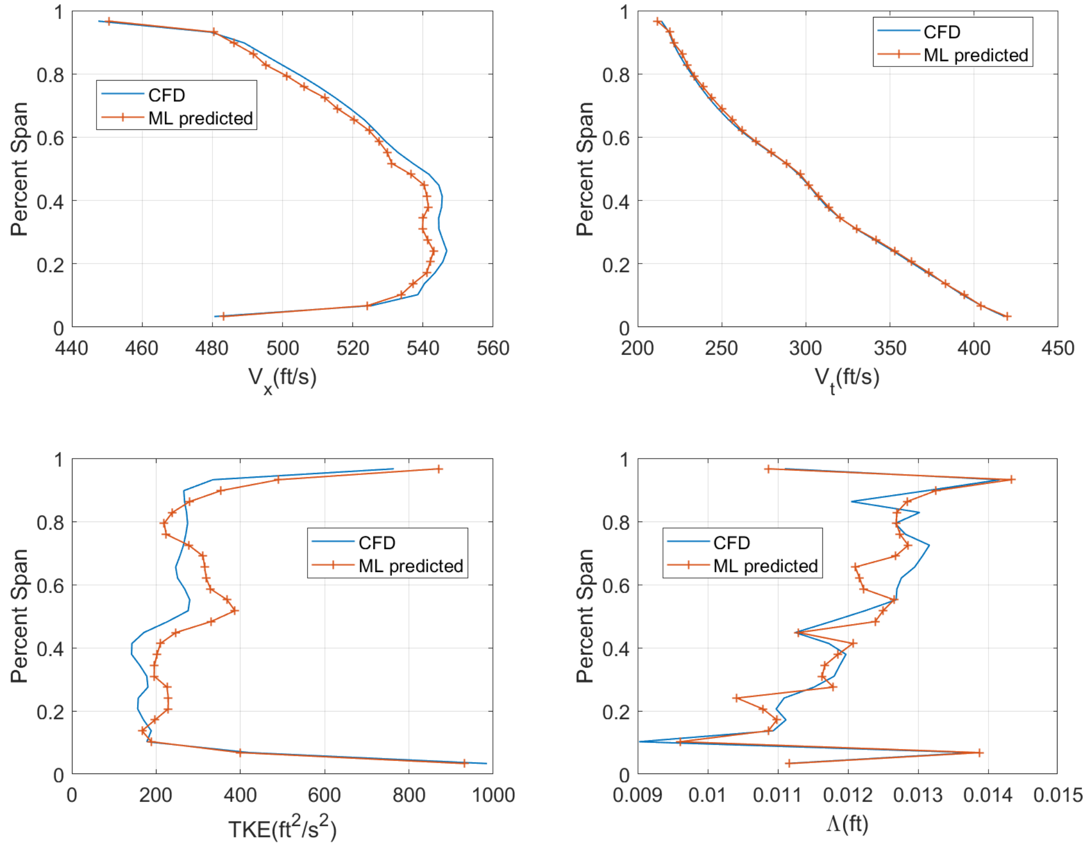
15 deg sweep @ 8860RPM, 80.8 lbm/s



Results are very good – low MSE, high R^2

Machine learning for swept wake flow

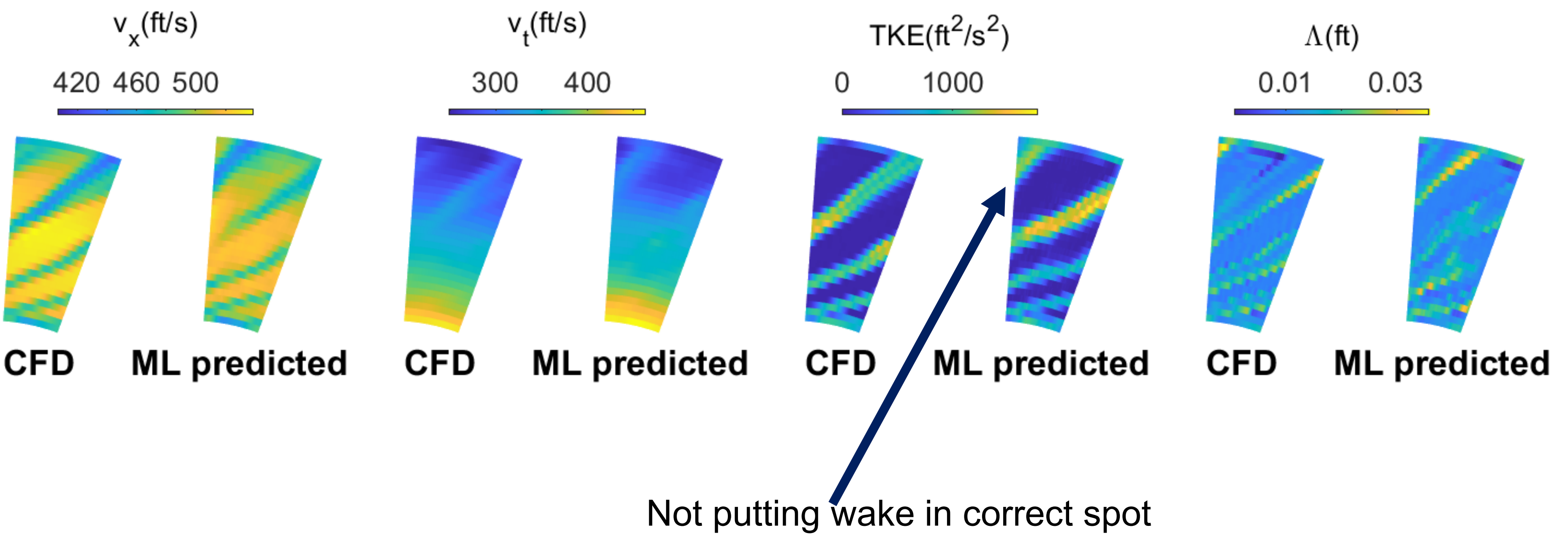
15 deg sweep @ 8860RPM, 80.8 lbm/s



Machine learning for **leaned** wake flow

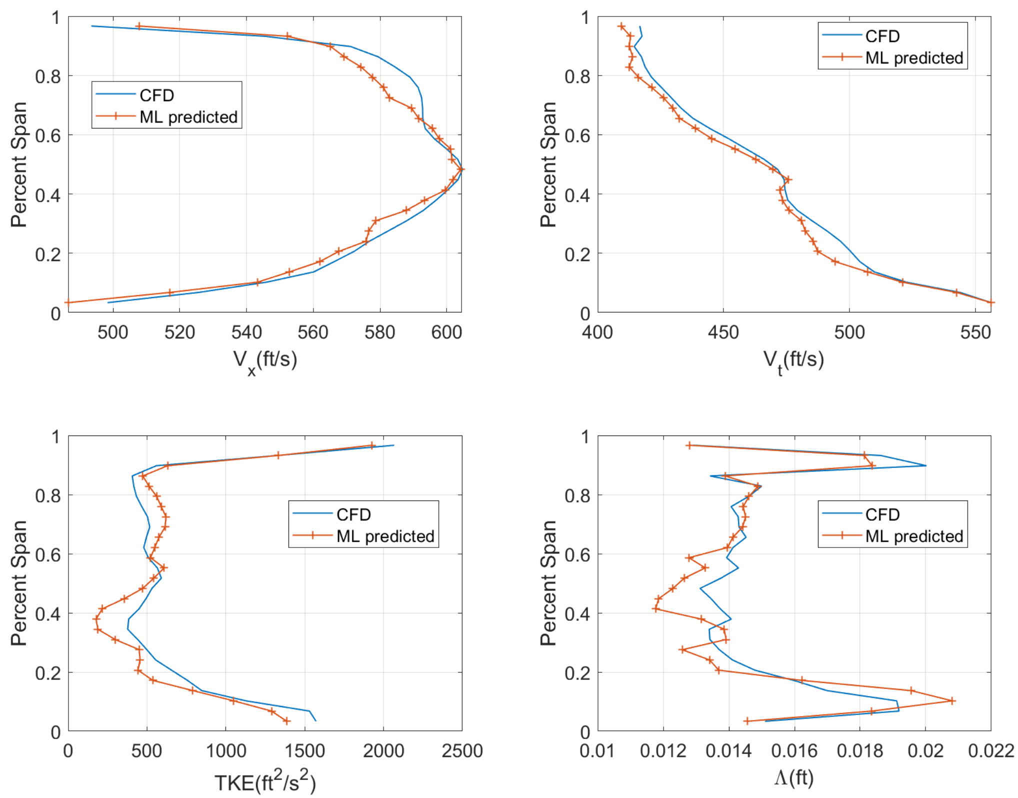
Database : SDT cutback hot and leaned new geometries (no swept cases)

15º lean @ 9809 RPM, 80 lbm/s, x=7.26”



Machine learning for leaned wake flow

15^{o} lean @ 9809 RPM, 80 lbm/s, x=7.26”



Machine learning for wake flow

What's left to do …

Must understand necessary inputs, may not be including important feature
Must understand if passage has to be extended for leaned cases

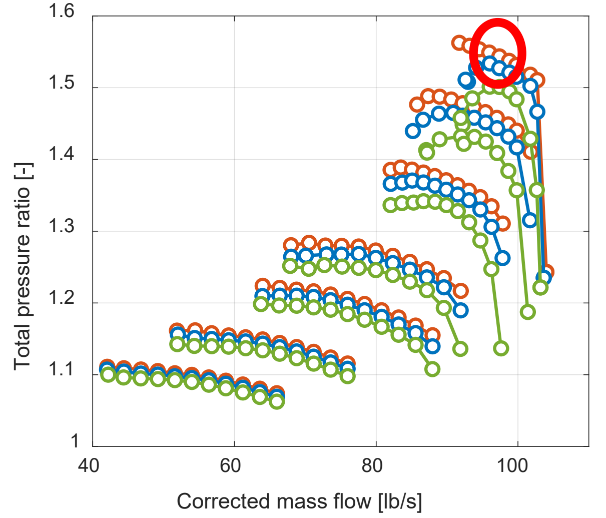
Must allow for different sized fans and ducts

Interesting insights : e.g. fan boundary layer thickness not important parameter

Production of database using RANS enables examination of acoustic outcomes in parallel to developing the machine learning

Assessment of cases in the database

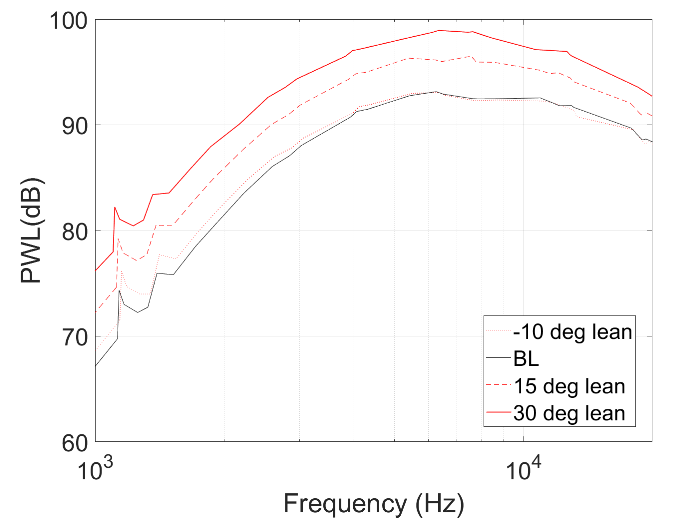
For a given fan geometry we have performance curves like this



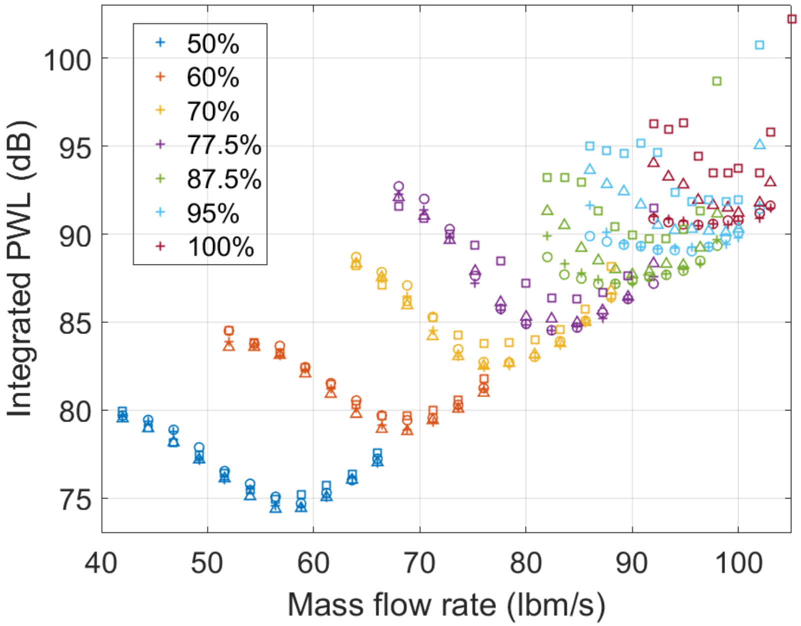
Just under 70 cases. For each case, we need the 4 wake flow parameters used as input for the acoustic calculation

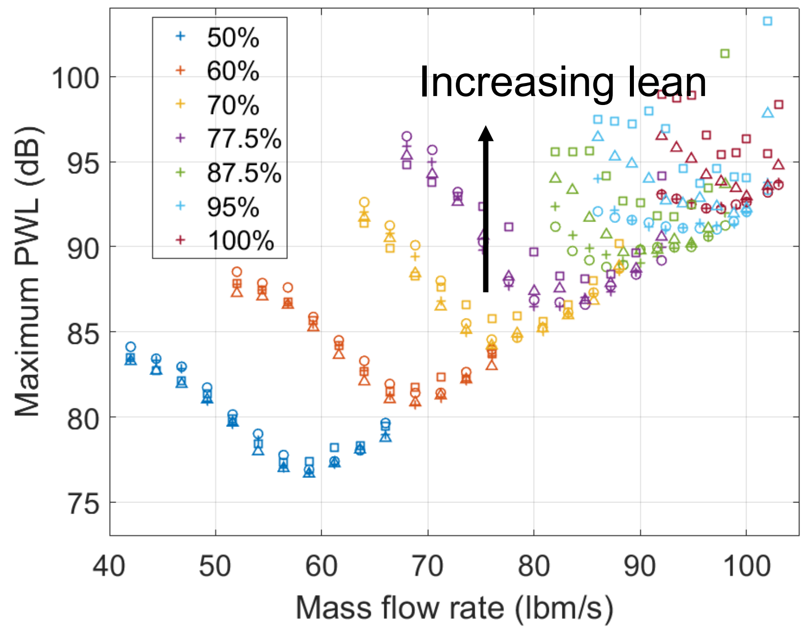
Then, for each case we get an output acoustic spectrum

100% speed 92 lbm/s case.
RANS data as input for acoustics



Assessment of cases in the database: lean





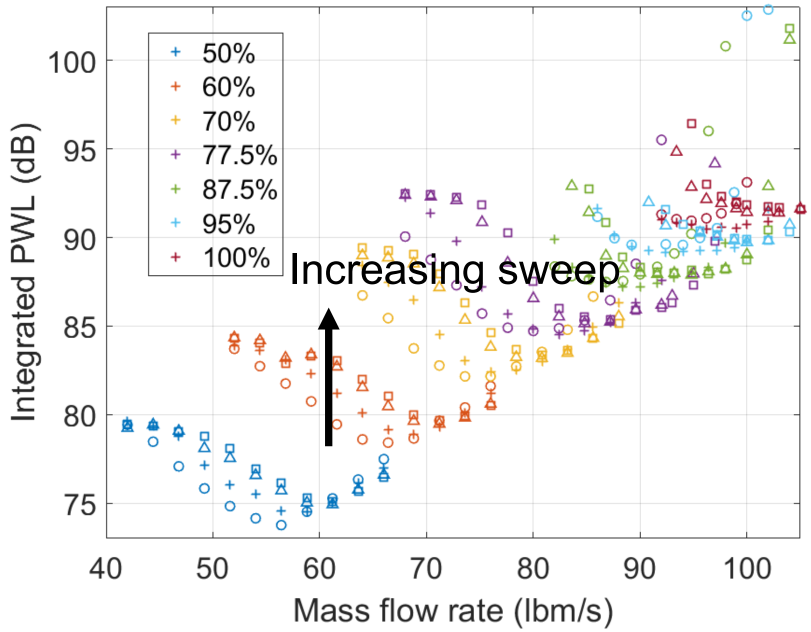
Circles: -10 ° lean
Crosses: 0 ° lean
Triangles: 15° lean.
Squares: 30 ° lean

Lean doesn't affect low frequency

Differences are driven by turbulence intensity

Assessment of cases in the database: sweep

Circles: -15° sweep
Crosses: 0° sweep
Triangles: 15° sweep
Squares: 20 ° sweep



Differences are driven by turbulence length scale

Lean and sweep results to be validated this summer

RANS based input used for these acoustic calculations
Shows power of method, if machine learning could provide the wake flow characteristics

Summary and future work

Wake parameter surrogate model - will enable broadband noise as design consideration

All initial findings show promise for this capability. CNN architecture same for all parameters.

Increased database, including larger differences in fan geometry still working reasonably well

Will continue to add different fan geometries and study outcomes : different radial extent, different # of blades

Noise prediction (focus on low-order FEGV response)

Lean affects noise at higher speeds (turbulence intensity is driver)

Sweep has smaller affect but at all speeds (length scale is driver)

Still to come

Validation of low-order prediction for full scale fans

Can low-order be modified to handle asymmetry in inflow to stator caused by nonuniform inflow to the rotor

Questions ?