Project 075 Improved Engine Fan Broadband Noise Prediction Capabilities

Boston University & Raytheon Technologies Research Center

Project Lead Investigator

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University Participants

Boston University (BU)

- P.I.s: Sheryl Grace – Associate Professor, Mechanical Engineering
- FAA Award Number: 13-C-AJFE-BU Amendment 022
- Period of Performance: November 1, 2023, to October 30, 2024
- Tasks:
  1. Fan-wake surrogate model creation
  2. Improved low-order model
  3. Rig test planning

Project Funding Level

Year 3 Funding (January 1, 2023, to June 1, 2024):
Federal Aviation Administration (FAA): $400,000 total ($150,000 to BU, $250,000 to Raytheon Technologies Research Center [RTRC])
Matching Funds: $400,000 total ($200,000 from BU [datasets, faculty time, graduate student stipend], $200,000 from RTRC [personnel time, Pratt & Whitney® (P&W)])

Year 4 Funding (March 18, 2024, to May 31, 2025):
FAA: $201,044 total ($105,286 to BU, $95,758 to RTRC)
Matching Funds: $201,044 from BU (datasets, AeroAcoustics Research Consortium [AARC] previous funding, faculty time)

Investigation Team

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Nuo Li, graduate researcher (PhD), Tasks 1 & 2
Theo Favier, graduate researcher (Master of Science [MS]). Tasks 1& 2
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Raytheon Technologies Research Center
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Julian Winkler, Tasks 1, 2 & 3
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Matt Kennedy, Task 3

Project Overview

The noise signature of contemporary turbofan engines is dominated by fan noise, both tonal and broadband. Accepted methods for predicting the tonal noise have existed for many years. Furthermore, engine designers have methods for controlling or treating tonal noise. This is much more challenging for broadband noise. Thus, it is clear that further reductions in engine noise will require accurate prediction methods for the broadband noise to enable design decisions. Interaction noise from the fan-stage is a dominant broadband mechanism in a modern high bypass engine and is created by the interaction of the turbulence in the fan-wakes with the fan exit guide vanes (FEGVs). This project leverages prior development of low-order models for the prediction of fan broadband interaction noise. Gaps in the low-order approach are addressed based on knowledge gained from computation and experimentation. In particular, a method for determining the inflow into the stator via a machine learning (ML) algorithm is being developed. The low-order method will also be validated against full- and rig-scale data and appropriate development undertaken based on the findings.

Task 1 - Fan-wake Surrogate Model Creation

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Objective

The objective of this task is to build a surrogate model using machine learning that will work with performance level unsteady Reynolds-Averaged Navier-Stokes (URANS) to specify the mean flow, turbulent kinetic energy, and turbulent length scale at locations along the helical fan-wake path.

Research Approach

Subtask 1.1&2: Development of Autoencoder & Development of Decoder

The ML was applied to this problem in Year 4 of the ASCENT Project 075 and our team continued to use the decoder part of a neural network. Four wake flow parameters are learned in the region downstream of the fan. The mean flow axial and circumferential velocities and the turbulent kinetic energy and turbulence length scale are learned using a two-dimensional (2D) Convolution Neural Network (CNN). In the 2D method, the data are made of axial slices of the wake flow.

TensorFlow® is used for the ML and is integrated into a Python® wrapper. In Year 4, the CNN was improved and evaluated against alternatives. One improvement was in the number of interpolated points on the 2D axial slice of wake data. By selecting 64 points in the circumferential direction and 64 in the radial, the image being constructed with the ML breaks down much more easily and the sizes of the different ML layers are more easily fit.

Subtask 1.3: Identification & Creation of Training Data

The focus of Year 4 was *Subtask 1.3b: Creation of additional training data.* A collaborator from the Institut Supérieur de l'Aéronautique et de l'Espace (ISAE-Supaero) in Toulouse, France, was also identified during the Year 3. Professor Bauerheim's team has been developing canonical fan geometries with some basis in existing rig-scale fans that have been tested in the past. His group has also performed rotor-alone type RANS simulations for the fan geometries they have developed. A data usage agreement was sought but it continued to stall. Finally, Professor Bauerheim made much of his data open-source. The ISAE team found a way to share their RANS results for 59 different fans with the ASCENT Project 075 team. The results of our initial ML applied to this new database are included as an appendix in the form of the American Institute of Aeronautics and Astronautics (AIAA) aviation abstract that describes the work. In short, the ML works exceptionally well with this database.

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Additionally, to increase the database for the ML, BU PhD student Nuo Li learned how to implement the SU2[1] computational software. However, it was shown that the turbulence model did not give adequate results for use in building the needed turbulence length scale. Subsequently, the Cadence® Fidelity® Flow[2] was acquired. The team at BU can now run fan-alone simulations using Cadence Fidelity Flow. The results are still being analyzed to determine if the turbulence parameters are well behaved. It is assumed this software will work because of its similarity to the previously used FINETurbo[3] software that ISAE applied for their RANS analysis of their 59 fans.

Subtask 1.4: Application of Surrogate Model to Relevant Fan Geometries

The CNN ML predictions were applied to the previous database that contains the swept, leaned, and low blade count fans. And now it has been applied to the new database of 59 fans. It is of interest to know how the ML learned parameters work together with the low-order acoustic method to predict the final expected power level in the bypass duct for the cases. Last year's report showed how this played out for the original database. The use of ML learned parameters for analysis on three of the new fans is shown in Appendix A. Based on the results of the analysis in Appendix A, either direct RANS inputs or ML inputs can be used together with the low-order model with similar outcomes. The cases for which ML does not achieve the desired modeling outcome include fan geometries or operating points that require extrapolation from the database, which is expected.

The ability to consider the noise from so many different fan stages has led to further insights into fundamentals of fan stage broadband interaction noise. From the original database, the overall sound levels were viewed as they related to the fan efficiency plots as shown in Figure 1. The lowest noise point along any speed line does not line up with the highest efficiency point. It can also be seen by the black dots that the three main operating points that are the focus of testing and simulation—approach, cutback, and takeoff—are not at high efficiency points nor at low noise points.

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[1] SU2 is an open-source collection of software tools written in C++ and Python for the analysis of partial differential equations (PDEs) and PDE-constrained optimization problems on unstructured meshes with state-of-the-art numerical methods.

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[2] Cadence Fidelity Flow is a computational fluid dynamics (CFD) platform allows for the simulation of a wide range of complex fluid dynamics problems, such as multiphase flows, reactive flows, and turbulent flows, from industrial to academic applications.

[3]Stand alone FINETurbo used by ISAE. Originally developed by NUMECA before being purchased and modified by Cadence (https://www.numeca.de/en/news/fine-turbo-version-17-1/).

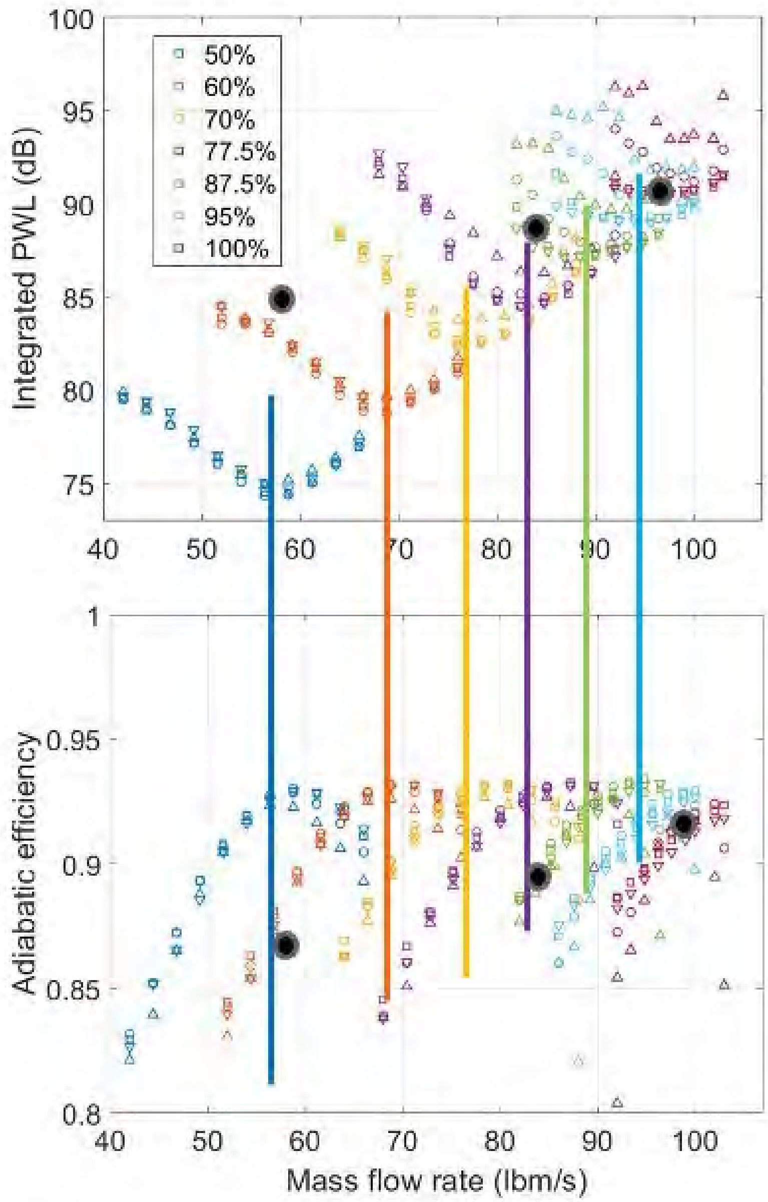

Figure 1. Top: Downstream noise. Bottom: Fan efficiency. Different leaned fans with same FEGV: Downward triangles: -10∘. Squares: 0∘ (BL). Circles: 15∘. Upward triangles: 30∘

The new dataset does not have complete operating lines. Four-Five operating points are available for any given fan as shown in Appendix A. Thus, for the new database, the same type of comparison between the low noise point and max efficiency cannot be completed. However, the investigation led to an effort to identify the relationship between noise and efficiency. To this end, different Mach number scalings (M^n with different n values) were evaluated and a collapse in the data was found when n=5. The broadband noise was analyzed in 1/3 octave bands and over the entire spectrum. The scaled values are shown vs. efficiency for the 59 fans in the new database. Single trend lines seem to be appearing. This means that a very simple algebraic method for estimating the overall broadband noise of a fan-stage based on the fan efficiency may be available in the future. This would be a very useful design tool.

Milestones
- Validated and refined the ML surrogate model.
- Improved the ML model and applied the model to a new database with success.

Major Accomplishments
- Improved the 2D CNN models for fan wake parameter prediction.
- Applied ML to a new dataset.
- Completed acoustic analysis using the low-order method of all of the fans in the new database.
- Evaluated SU2 and Cadence flow software to provide a method for creating and analyzing additional fans in the future.

Publications
Li, N., Zhange, Y., Winkler, J., Reinmann, C. A., Voytovych, D., Joly, M., Lore, K. G., Mendoza, J., & Grace, S. M. (2024). Development of fully low-order prediction of fan broadband interaction noise via integration of machine learning. *AIAA Journal, 62*(6). https://doi.org/10.2514/1.J063148

Li, N., Winikler, C., Reinmann, A., Voytovych, D., Joly, M., Lore, K. G., Mendoza, J., & Grace, S. M. (2023, June 12-16). *Machine learning aided fan broadband interaction noise prediction for leaned and swept fans* [Conference paper]. AIAA AVIATION 2023 Forum, San Diego, California, Virtual.

Outreach Efforts
- Presented at several university seminars and highlighted this work, including Embry Riddle University (November 2023), Virginia Tech (September 2024), and University of California (UC) Irvine (November 2024).

Awards
None.

Student Involvement
Nuo Li, graduate researcher (PhD) develops the ML and adopted and tested the two possible CFD codes, Theo Favier, graduate researcher (MS) worked on defining the thickness geometry for the fans in the new dataset, and Amarylis Wiltz, undergraduate researcher, ran parametric studies to help tune the ML method.

Plans for Next Period
- Continue refinement and validation of the ML surrogate model.
- Develop and add additional fans to analysis.
- Consider scenarios for when the database includes fans with different flow paths (fans with differing radial extents) and how ML is implemented and performs under these conditions.
- Consider combining the two databases.

Task 2 - Improvement of Low-order Model
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Objective
The objective of this task is to validate the low-order method against full-scale test data. The existing low-order methods are regularly applied to the Source Diagnostics Test (SDT) cases and as such have been well validated against this test, which represents one scaled fan and multiple FEGV configurations. The low-order method might also require reformulation to account for other real-flow effects.

Research Approach
Subtask 2.1: Ability to Predict Full-Scale Results

The low-order method will be applied to a full-scale geometry with available validation data. Due to the difference in frequency range of interest for the full-scale case, as compared to the scaled fans, it is surmised that the low-order method will require grid adjustments and integral extent adjustments. Such improvements to the low-order method will be completed as part of this task.

The test of the low-order method related to the FAA Continuous Lower Energy, Emission and Noise (CLEEN) Program I rig, and full-scale engine demonstration cases are still in progress. While this effort did not get attention this year, it remains in the background as something that must still be addressed. The results did not indicate that the low-order method performed well for the full-scale setting.

Acquisition of a computational fluid dynamics (CFD) tool at BU during this past year will aide in moving this investigation forward. Our team will perform analysis on the SDT fan stage for both the rig and full-scale setting. The acquisition of this CFD tool will allow for investigation of the questions that arose when analyzing the CLEEN fan.

A focus in Year 4 was improving the capability for the low-order method to handle FEGV sweep. The core cascade solver and its integration into the broadband noise calculation was studied carefully. The method by which sweep is characterized internally in the calculation was updated and the results improved. This improvement also allowed the low-order method to be used to study the impact of FEGV placement downstream of the fan on the fan-stage noise. In this study, the BU-Rotor-Stator Internation (RSI) code was verified against an alternative low-order method (referred to here as the Hanson method). It was through an agreement with Optis that their software OptiSound® was purchased and used to obtain the Hanson method predictions. The outcomes of this study were presented at the Aeroacoustics conference in 2024 (Li et al., 2024, listed under publications below).

The most important outcomes from the study are:

1) The BU-RSI and Hanson method do not react to changes in the mean flow in the same way. The BU-RSI has a stronger reaction to mean flow acceleration.
2) The BU-RSI and Hanson method do not react to changes in the length scale exactly the same. The Hanson method tilts the spectrum more as length scale changes.
3) Both methods, the BU-RSI and Hanson method, predict that as the SDT FEGV is moved very close to the fan, the overall broadband interaction noise only changes by about 1dB.

In Year 2, *Subtask 2.2: Inclusion of Tip Flow Impact on the Low-Order Model* and *Subtask 2.3: Inclusion of Inflow Distortion Impact on the Low-Order Model* were discussed.

Milestones

- Validated the low-order model on new geometry, specific the test rig-scale vs. full-scale applicability. The low-order method has been improved to more accurately model swept vane cases (which is the case for both the AneCom AeroTest 1 (ACAT1) and the FAA CLEEN I geometries). The low-order method was verified against the Hanson method (some differences were seen). It was applied to study the effect of moving an FEGV closer to the fan and the results indicate that there is little broadband noise penalty to shortening the interstage gap.
- Completed final improvements to low-order model. The low-order model has been applied to several cases that have accompanying experimental data for validation: (a) the ACAT1 geometry and now to the FAA CLEEN I rig- and full-scale geometries, and (b) the rig-scale cases, ACAT1 and FAA CLEEN I, show good agreement between the predicted and measured acoustics. In all cases, the approach prediction is slightly high. The source of this discrepancy is not understood yet. The FAA CLEEN I full-scale case has not been accurately predicted.

Major Accomplishments

- Obtained the RANS solver that works for fan alone simulation to provide the opportunity for studying the rig scale vs. full-scale setting noise scenario in the future.
- Acquired and used OptiSound software to verify BU-RSI method.
- Improved the method for accounting for FEGV sweep in the low-order acoustic method.
- Completed a computational study of FEGV placement.

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Publications

Li, N., Winkler, J., Reinmann, C. A., Voytovych, D., Mendoza, J., & Grace, S. M. (2024). Effect of straight and swept FEGV placement on fan broadband interaction noise. In *30th AIAA/CEAS Aeroacoustics Conference (2024)* (p. 3161). https://doi.org/10.2514/6.2024-3161

Outreach Efforts

- Discussed this topic in presentations at Virginia Tech and UC Irvine in Fall of 2024.

Awards

None.

Student Involvement

Nuo Li, graduate researcher (PhD), worked on the low-order model.

Plans for Next Period

- Update the low-order model dependent on the results of the full-scale studies and perform further comparisons to the OptiSound results.
- Complete final improvements to low-order model.

Task 3 - Rig Test preparation

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Objectives

The objective of this task is to perform experiments in the RTRC Acoustic Research Tunnel (ART) to (a) acquire key aerodynamic and acoustic data to support the validation of low-order and mid- (RANS) to high- (VLES, LBM Very Large Eddy Simulation, Lattice Boltzman Method) fidelity CFD models, and (b) assess the noise trends and scaling laws of different fan stage.

Research Approach

RTRC began designing the rig for the planned experiments. After careful study, it was concluded that additional funds were necessary in order to fully design the desired rig and complete the experiments. A stop work was ordered related to the fan rig development while a new proposal was developed that outlined the funding needs. The proposal was submitted and approved. Once it was approved, funding was issued and work recommenced.

The rig being designed is a scaled version of the P&W Fan Rig 2 from the FAA CLEEN I program. The flow path will focus solely on the bypass, thus eliminating the need for a core. The configurations that are planned include the P&W baseline design, as evaluated at the National Aeronautics and Space Administration (NASA) previously, and either a rotor-alone (no FEGV) configuration or a shifted FEGV configuration.

As Year 4 concludes, the fan and hub design will be completed, and fabrication will be sourced. The FEGV and bifurcations have preliminary layouts. The nacelle aerodynamic design is complete, and the mechanical design is in progress allowing for additive manufacturing considerations. The electric motor drive from previous programs is being adopted.

The Gantt chart for the project (Figure 2) shows the best estimate for completion of the tests.

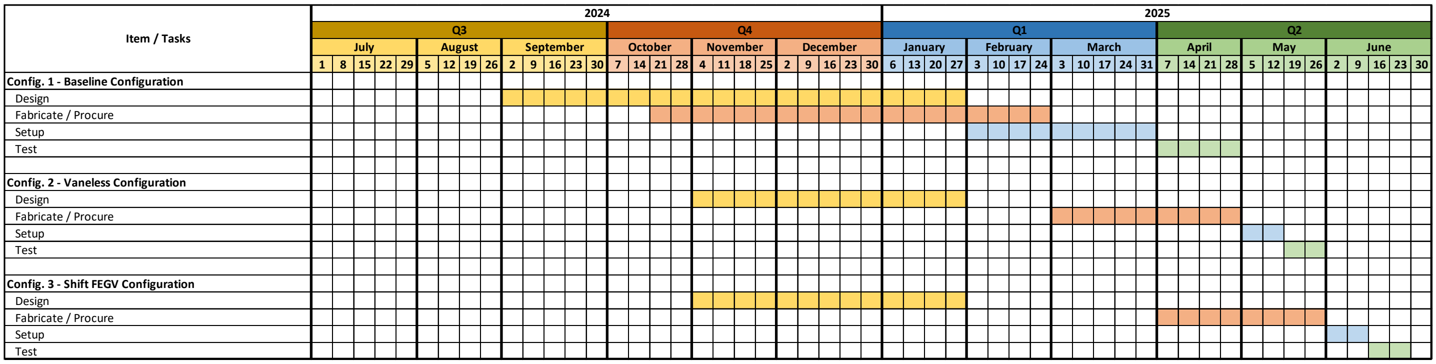

Figure 2. RTRC rig development and test schedule.

Meetings have commenced to discuss in detail the flow and acoustic data acquisition. The final test matrix will be developed as the rig comes together.

Milestones

- Continued ongoing final rig design.
- Test rig shakedown and complete rig testing. The rig will be built in early 2025 and the tests will commence around May 2025.

Major Accomplishments

- Participated in multiple meetings between RTRC/BU and P&W to determine the exact test capabilities.
- Determined the specification of additional funds needed to fully design and complete the rig test.

Publications

None.

Outreach Efforts

None.

Awards

None.

Student Involvement

None.

Plans for Next Period

- Test rig shakedown.
- Complete rig testing.

APPENDIX A

Low-Order Methods for Analysis of Impact of Fan Design on Fan Stage Broadband Interaction Noise

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The fan stage is a dominant source of noise in modern high-bypass ratio engines. Fan blade design plays a crucial role in both fan stage aerodynamic performance and noise. This work explores the impact of fan blade design on the fan stage downstream propagated broadband rotor-stator interaction (RSI) noise using low-order methods. A dataset with 59 fan blade geometries at multiple operating points is used as a basis of this study. A RANS-informed cascade model is used to predict the broadband interaction noise. A generative machine learning model is employed to explore operating points not available in the original dataset. Fan isentropic efficiency is shown to be inversely proportional to the fan stage broadband interaction noise when the integrated sound power is scaled by M^6.

I. Introduction

Increase in bypass ratio (BPR) and decrease in fan pressure ratio has became a major design trend in modern and future turbofan engines for better efficiency. The design trend has led to a shift of the dominant broadband noise source from jet noise to fan noise.

Resolving the broadband acoustic signal numerically requires computationally expansive simulations such as Large Eddy Simulation (LES) [1, 2] or Lattice Bolzmann Method using Very large Eddy Simulation (LBM/VLES) [3, 4]. The early design phase of an engine can benefit from more efficient low-order models [5–8]. In this work, the focus is on a low-order model for the rotor-stator interaction (RSI) broadband noise, which is a major source of fan-stage noise. The low-order model relies on the mean fan wake velocity and turbulence quantities upstream of the Fan Exit Guide Vane (FEGV). These can be obtained from lower fidelity simulations such as steady Reynolds averaged Navier-Stokes simulations(RANS).

RANS is widely utilized in engine design due to its lower cost and ease of automation when coupled with modern gridding softwares. Still there is a push to further speed up the low-order predictions. A method that has been considered is surrogate fan wake models using machine learning (ML). Such a ML method was demonstrated in a previous study [9]. In Ref. [9], a generative convolutional neural network (CNN) model was introduced to predict the mean flow and turbulence quantities in the fan wake. Ref. [10] utilized a U-net based CNN model with upsampling to determine the flow in a multistage compressor.Ref. [11] demonstrated an application of a U-net based model to predict fan wake entropy and fan efficiency.

This study extends the research presented in Ref. [9] by applying the ML to the fan database described in Ref. [11] and provided by Fesquet et al. from ISAE-SUPAERO. The fan database is also used to study the broadband noise produced by the multitude of fan geometries in the database. The broadband noise is computed using the BU-RSI cascade model [12] with RANS based fan wake flow input. The acoustic trend and its associated correlation with rotor alone efficiency will be discussed. The generative ML model is then used to obtain the fan wake input needed for the acoustic calculation at operating points not available in the database.

II. Method

The current dataset consists of RANS fan-alone simulations for 59 fan geometries at several operating points on 4 speed lines totaling 298 cases. Examples of 9 fan geometries are depicted in Fig. 1. The dataset was provided by Fesquet et al. [11] and is derived from 6 main rotor geometries: the Akira DGEN-380, NASA R37 and R67, the Safran LP4 fan, EC Lyon ECL5, and ISAE-SUPAERO PropHyDis. The final geometries are all 14-blade fans generated by interchanging the design parameters of the original geometries and fitted into the 352mm-diameter duct associated with

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the DGEN-380 fan stage. The steady-RANS simulations were set up using fan alone, periodic domains and employ the Mentor's $SST k-\omega$ turbulence model [13]. The Cadence Fine/Turbo Euranus solver was used for the simulation and Cadence Autogrid5 was used to create the mesh.

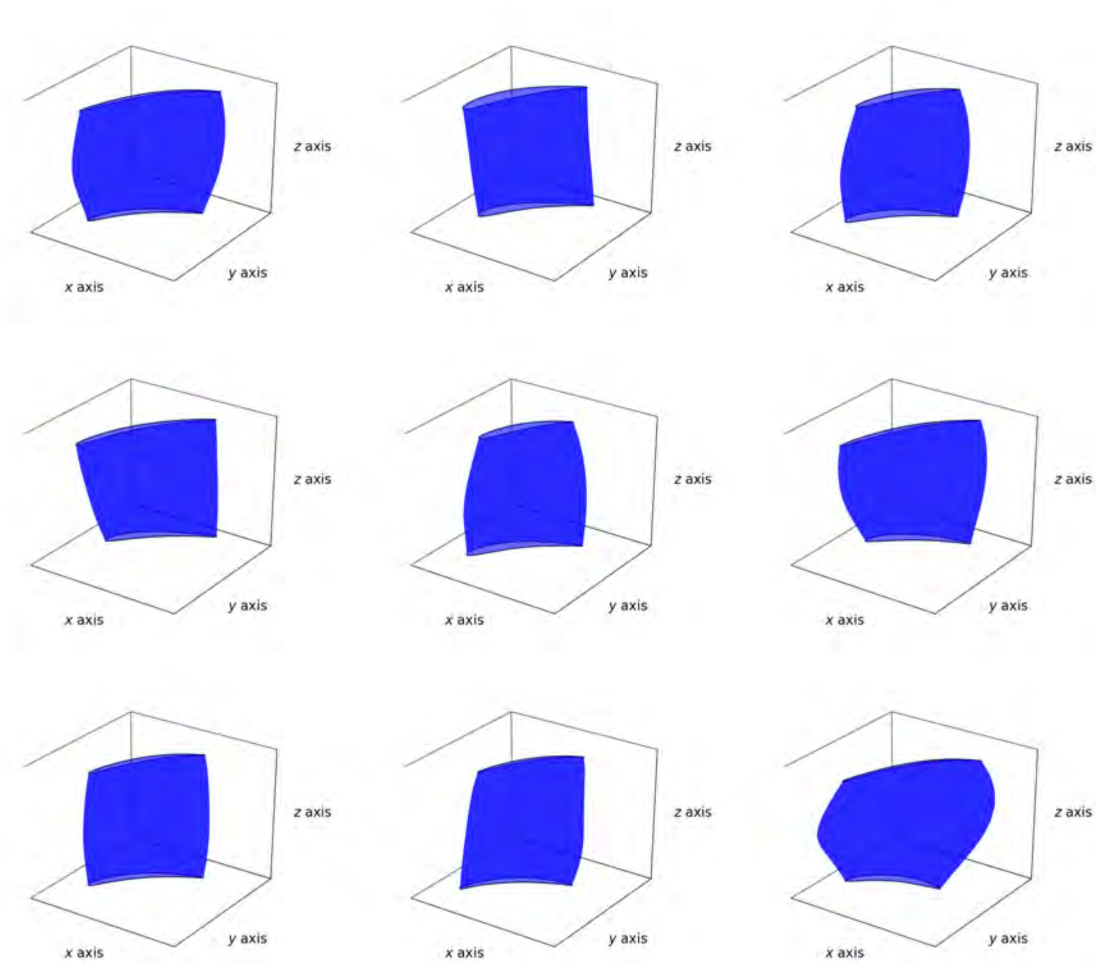


Fig. 1 Example blade geometries

An FEGV must be defined to complete the fan stage in order to consider interaction noise. The FEGV geometry has been created by modifying the NASA SDT baseline vane based on basic information available for the DGEN-380[14]. In particular, the FEGV has 40 vanes and a chordlength of 1.28in (0.0033m). In the low-order method, FEGV radial strips from hub to tip are transformed into flat-plate cascades and analyzed. As such, the flat plate geometry at each radial location is defined with the same global stagger profile as the SDT.

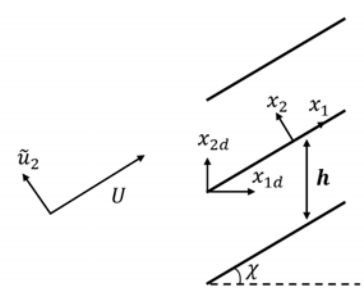


Fig. 2 Linear cascade definition

The acoustic result is computed by the cascade model based on Ventres et al. [8] and later expanded and improved by Envia & Nallasamy[15], and Grace [12]. The simulation is carried out in the frequency-wavenumber domain. The model considers a linear, 2-D flat plate cascade interacting with a turbulent wake carried by the mean flow U as depicted in Fig. 2. The unsteady blade loading depends only on the disturbance normal to the vane, which has the form $\tilde{u}_2(r, \mathbf{k}, \omega)e^{i\mathbf{k}(z\cos\chi x_1 - sh\sin\chi x_2)}$ where $\mathbf{k} = (k_1, k_2, 0)$ and s is

the vane index. The vane loading distribution $\tilde{f}(r, z, \mathbf{k}, \omega)$ can be
obtained by solving the integral function

$$e^{i\mathbf{k}z} = \int_{b}^{-b} K_c(z - z')\tilde{f}(z, \mathbf{k}, M)\frac{dz'}{b} \quad (1)$$

where K_c is a kernel function derived in [8], and z is the coordinate along the chord. This vane response to a unit amplitude disturbance is convolved with the turbulence statistics to obtain the expected value of the vane response [8]. The Liepmann turbulence spectrum [16] is used to model the fan wake turbulence in the frequency-wave number domain. The duct acoustic power is then computed via Green's method for every cut-on circumferential and radial mode.

Previous study using this model [12, 17] showed that the computed sound power level is highly dependent on the definition of the vane stagger angle χ: a larger stagger angle will lead to a higher sound power. However, it was also shown that the acoustic trends with fan RPM and fan wake turbulence levels etc. are consistent given any stagger definition.

The low-order broadband interaction noise calculation is dependent on the cicumferentially-averaged values of mean axial velocity (v_x), mean tangential velocity (v_t), turbulence intensity (u'), and turbulence length scale (Λ) upstream of the FEGV. Isotropic turbulence is assumed so that when these input parameters are derived from RANS data, $u' = \sqrt{2/3TKE}$ and turbulence length scale is determined by $\Lambda = 0.43\frac{TKE^{1/2}}{0.09\omega}$.

While the acoustic model is often informed by input extracted from RANS. Earlier study [9, 18] showed reasonable accuracy in acoustic predictions made by coupling the low-order acoustic calculation with a ML surrogate for the input. In that study, a fan dataset was created with 8 fans of varying lean and sweep. Now, the generative CNN model is being applied to a new dataset with more fan design variations.

The ML developed for the fan wakes utilizes only the decoder part of a CNN. The model takes the following blade design parameters and operating point information as inputs:

- Rotor RPM (0D)
- Mass flow rate (0D).
- Leading edge radial location (1D)
- Trailing edge radial location (1D)
- Relative leading edge axial location (1D)
- Relative trailing edge axial location (1D)
- Relative trailing edge circumferential location (1D)
- Chord (1D)
- Stagger (1D)
- Inlet metal angle (1D)
- Outlet metal angle (1D)
- Blade thickness at five chordwise control points (1D)

The 0D inputs are scalars and the 1D inputs are specified at several spanwise equally-spaced locations along the fan. Currently, 5 spanwise sections are used. This provides the latent space that would be produced by an encoder.

The training data are the fan wake flow parameters at 30 equally-spaced axial slices downstream of the fan between 0.06m to 0.22m as measured from the fan stacking axis. At each axial location, the RANS solution is interpolated onto 64×64 points in the circumferential and radial directions.

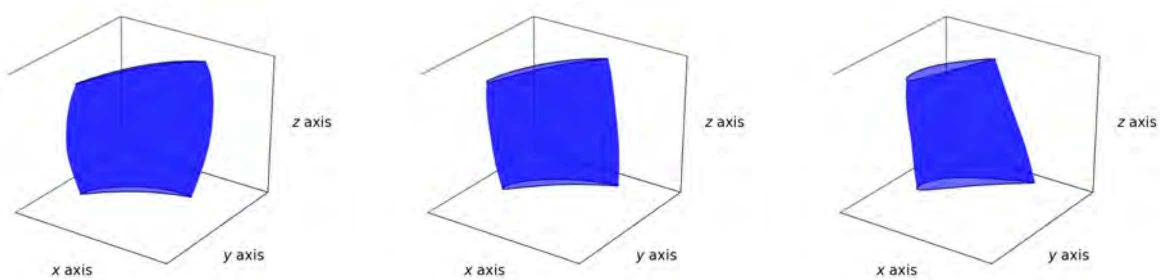
The inputs are concatenated into a 1D array for each axial slice in the training data. The concatenated input is followed by fully-connected layers to transform the input into a single 1/8 scale feature map (8×8 for the current output resolution). It is then passed to eight transposed CNN layers with three strided layers to expand the feature maps into 1/4 scale, 1/2 scale and finally the full scale output.

III. Results

The results for the ML model's performance on the new multi-fan dataset are discussed first. Three geometries were extracted from the dataset and reserved for testing. They are shown in Fig. 3. The training data then consists of the remaining 56 geometries. The model is trained in four channels for each wake flow parameter (v_x, v_t, TKE, Λ). Two mean error metrics are defined, both are averaged over an axial slice: (1) The relative error, e, is calculated by point-to-point difference on the full axial slice between the ML prediction and the CFD solution normalized by the averaged CFD value. (2) The circumferential averaged relative error, e_{circ}, is determined by first taking the circumferential averaged values for the ML prediction and the CFD, then, their differences are normalized by the slice averaged CFD value. In most cases, e_{circ}, is lower than e as it ignores any phase misalignment.

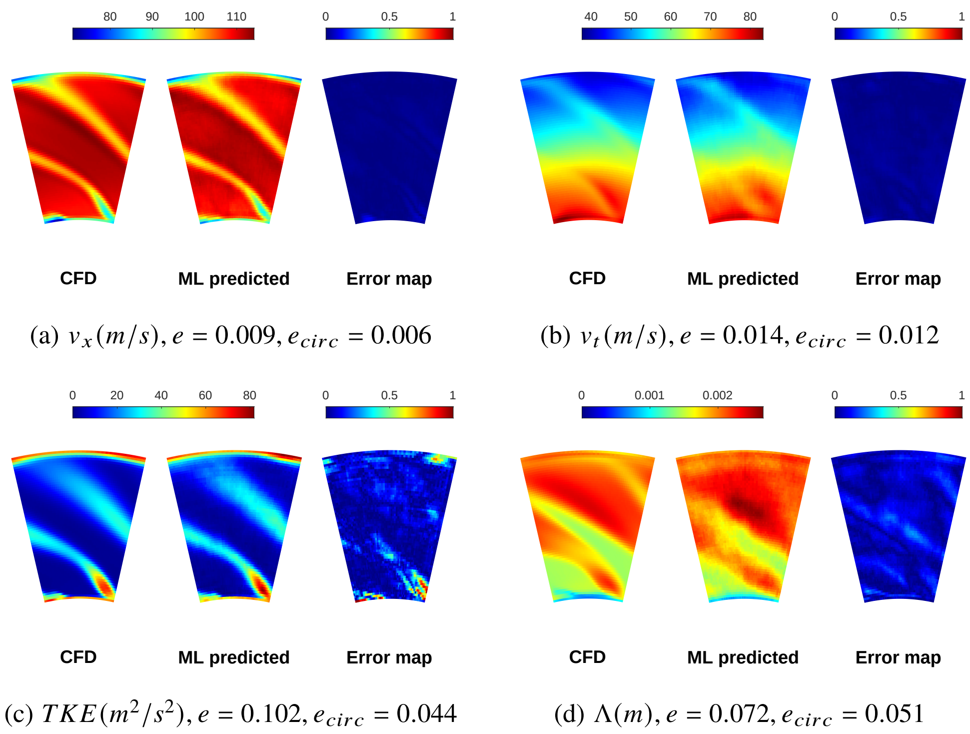
An example prediction for an axial slice near the FEGV leading edge is shown in Fig. 4 using test geometry 1 at 9000 RPM, 9.4 kg/s. The ML predictions exhibit good agreement with the target CFD solution exhibiting a 1% error for the velocity fields. The TKE relative error is notably larger than the velocity error mainly due to the scale of its variation between the wake center and background. The prediction errors for test geometry 2 are similar to test geometry 1 and examples are omitted for brevity. Test geometry 3 is a more challenging case due to its thicker profile which leads to large flow separation. It is considered a less preferable design. An example prediction for this geometry is shown in Fig. 5 at 12000 RPM, 9,84 kg/s, a slightly larger error is observed, but the model is still able to capture the wake profile. However, for an off-design, heavily stalled case, the results as seen in Fig. 6 are not good. This is considered the most challenging extrapolation case. The model completely fail to predict the wake under this condition. Previous studies [9, 18] have shown a very limited extrapolation capability using a generative CNN model. This is still true even with a more diverse dataset. Fesquet et al. [11] also noted that their transformative U-net failed to extrapolate the flow field for this stalled condition.

It is of interest to understand how an acoustic prediction using the low-order method is affected by using input either from RANS or from the ML surrogate model. As mentioned above, a single FEGV was created to complete the fan-stage for any fan in the dataset. In Fig. 7, the predicted broadband interaction sound power spectrum downstream of the fan stage with inputs from cases in figs. 4 to 6 are compared. The solid line shows the prediction when RANS data are used as input to the acoustic calculation and the dotted lines show the prediction when the ML surrogate model provides the input. The black and red lines show errors are less than 1 dB. This is typical for any fan geometry at an on-design operating point. For the heavily stalled case depicted by the blue lines, a very large error of more than 10 dB difference at 1 kHz arises. This is expected given that the ML prediction is very different than the CFD results for this case.



(a) Test Geometry 1 (b) Test Geometry 2 (c) Test Geometry 3

Fig. 3 Diagrams of test geometries



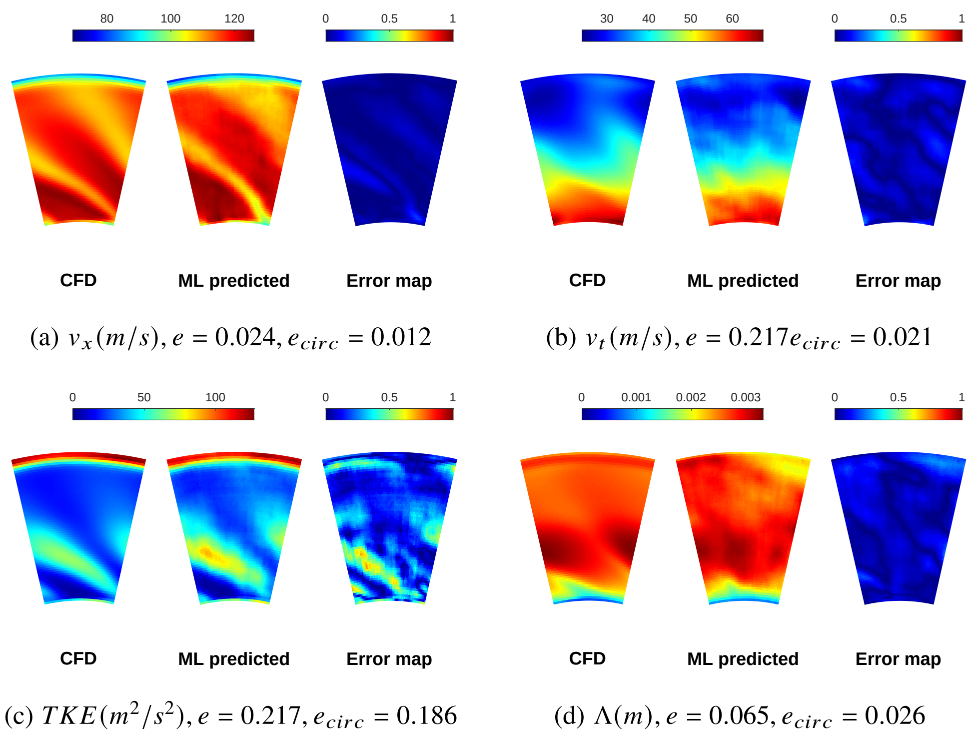
(a) $v_x(m/s), e = 0.009, e_{circ} = 0.006$

(b) $v_t(m/s), e = 0.014, e_{circ} = 0.012$

(c) $TKE(m^2/s^2), e = 0.102, e_{circ} = 0.044$

(d) $\Lambda(m), e = 0.072, e_{circ} = 0.051$

Fig. 4 Flow fields at axial slices upstream of FEGV. Test geometry 1 at 9000RPM, 9.4kg/s



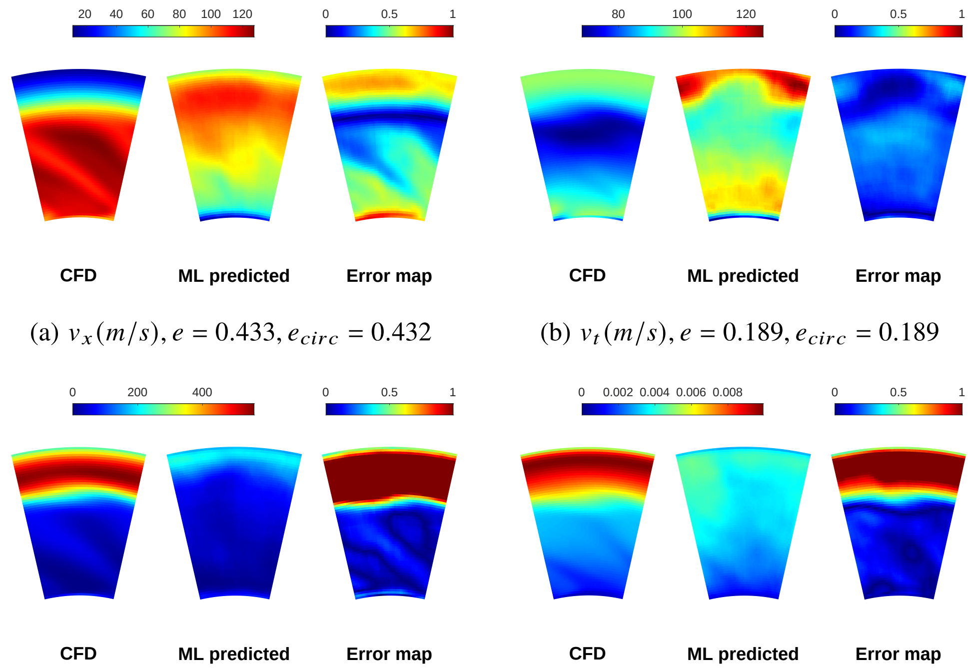
(a) $v_x(m/s), e = 0.024, e_{circ} = 0.012$

(b) $v_t(m/s), e = 0.217 e_{circ} = 0.021$

(c) $TKE(m^2/s^2), e = 0.217, e_{circ} = 0.186$

(d) $\Lambda(m), e = 0.065, e_{circ} = 0.026$

Fig. 5 Flow fields at axial slices upstream of FEGV. Test geometry 3 at 12000RPM, 9.84kg/s



(a) $v_x(m/s), e = 0.433, e_{circ} = 0.432$

(b) $v_t(m/s), e = 0.189, e_{circ} = 0.189$

(c) $TKE(m^2/s^2), e = 0.666, e_{circ} = 0.648$

(d) $\Lambda(m), e = 0.374, e_{circ} = 0.369$

Fig. 6 Flow fields at axial slices upstream of FEGV. Test geometry 3 at 15000RPM, 8.19kg/s

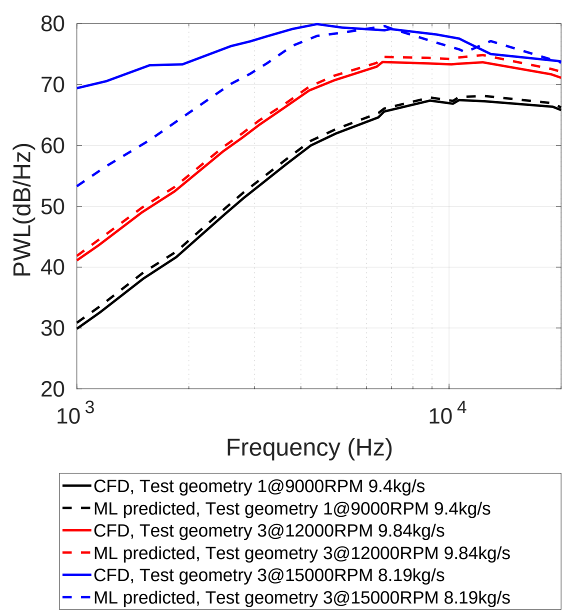


Fig. 7 Sound power spectra predicted using CFD and ML predicted inputs.

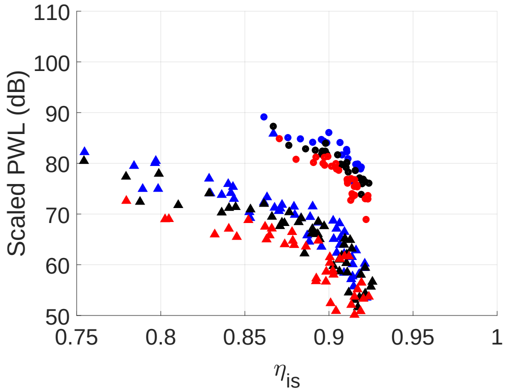
Access to the new fan dataset enabled a study of fan-stage acoustics that is discussed here. The results in this section were all obtained using the low-order acoustic method with input taken directly from the RANS simulations. The study was motivated by the expectation that there may be a correlations between fan performance and noise when considering multiple fan blade designs at different operating points. Indeed, in [17] it was found that the overall sound power level (OAPWL) does not perfectly mirror the isentropic efficiency curve for a single rotor. However, it was found in [18] that at any given operating point (mass flow rate and rotor speed), the OAPWL is inversely proportional to the fan efficiency for fans with different lean and sweep. In this work, the correlation is analyzed across the larger set of fan geometries. The original goal of the creation of this dataset was to sample geometries with largest physical distance possible among each other within a reasonable sample size as described in [11] by blending the design parameters from 6 main existing main geometries, which annihilated the original design point, and the operating points were determined by the flow coefficient $\hat{\phi}_p$. For most fans, at least two operating points with $\hat{\phi}_p = 0.3$ and 0.45 were simulated, in which their mass flow rates as well as thrust are different for each rotor.

In an effort to eliminate the effect of operating point in the correlation, a scaled sound power was considered. Previous studies suggested that gust-airfoil or gust-flat plate interaction noise is highly dependent on Mach number [19]. Some studies [20, 21] suggested a scaling exponent of 4-5.2 between the acoustic pressure and Mach number. Here, the scaled sound power level is defined as

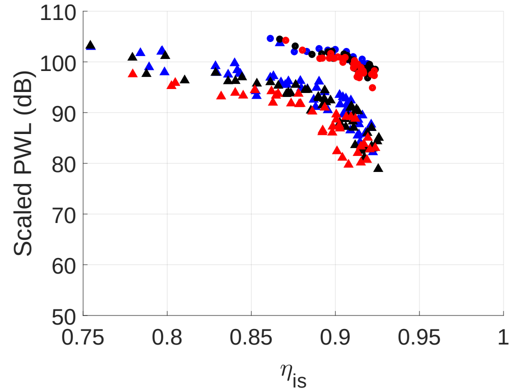
$$PWL_{scaled} = PWL + 10\log_{10}\left(\frac{M}{M_{ref}}\right)^6 \tag{2}$$

where M is the absolute Mach number upstream of the stator, and $M_{ref} = 0.3$ is the reference Mach number.

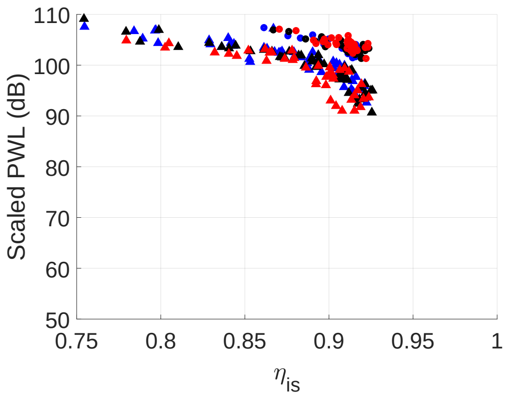
Figs. 8 show the scaled sound power level as functions of isentropic efficiency, η_{is} at four $1/3$ octave bands. The 1,250Hz nominal band is integrated from the range of 1,122Hz−1,413Hz, the 4,000Hz nominal band is integrated from 3,548Hz−4467Hz, the 8,000 Hz nominal band is integrated from 7,079Hz 8913Hz and the 12,500Hz nominal band is integrated from 12,220Hz−14,130Hz. Fig. 9 shows the overall sound power level integrated from 1,000Hz to 20,000Hz. Consistent trends can be observed showing a inversely proportional relation between sound power and fan isentropic efficiency for all geometries and operating points. The trends are nearly independent of fan speed represented by the marker color. Still, the slight shift in trend with respect to fan speed at low frequency, i.e. Fig. 9(a) indicates that the sound power scaling may be frequency-dependent. This will be further investigated in the final paper. Two distinct curves are observed representing two operating points with different $\hat{\phi}$ (which also implies different inlet flow angles at the leading edge of the FEGV). At higher frequency, i.e. Fig. 8(c) and Fig. 8(d), the scaled PWL becomes less dependent on both flow coefficient and isentropic efficiency. Trend lines fitted to these correlations can provide instantaneous design feedback pertaining to the expected broadband noise from a new fan design based on its operating curve.



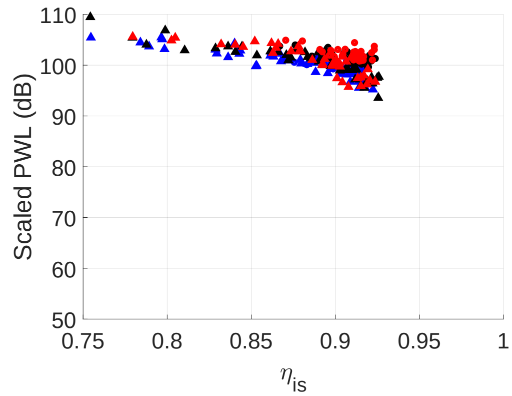
(a) 1,250 Hz



(b) 4,000 Hz



(c) 8,000 Hz



(d) 12,500 Hz

Fig. 8 Scaled sound power level as functions of isentropic efficiency at $1/3$ Octave bands. Blue:7000 RPM, black: 9000 RPM, red: 12000 RPM. Circles: low flow coefficient, triangles: high flow coefficient.

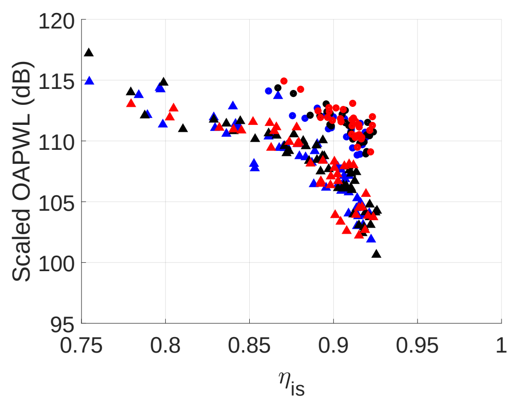


Fig. 9 Scaled OAPWL as functions of isentropic efficiency. Blue:7000 RPM, black: 9000 RPM, red: 12000 RPM. Circles: low flow coefficient, triangles: high flow coefficient.

IV. Conclusions and final paper

A study is performed to investigate the impact of fan blade design on fan-stage broadband interaction noise using low-order methods. The time-averaged flow field is supplied by steady RANS simulations of a dataset consisting of 59 fan geometries. It is shown that the Mach number-scaled aft-propagated interaction noise level is inversely proportional to the fan-alone isentropic efficiency. Additionally, a generative ML fan wake surrogate is assessed using the RANS fan solutions and the parameterized blade geometry as input. Promising results are obtained from the ML fan wake surrogate showing the capability to predicting the fan wake of a fan blade geometry at an on-design operating point.

The final paper will include a more detailed study of the sound power relation to the fan efficiency with fitted trendlines. Results from another fan stage configuration with larger diameter, NASA SDT, and other blade geometries designed based on the SDT may be considered for comparisons. Additional RANS simulations may be performed using Cadence Fidelity Turbo for more fan geometries and operating points.

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