Far Field Combustion Noise from Full-Scale Flight Tests

Eric H. Nesbitt[1], Ian A. Clark[2], Yueping Guo[3] and Russell H. Thomas[4]

NASA Langley Research Center, Hampton, VA 23681, USA

This paper presents the development of a new combustor noise prediction process for direct combustion noise. This process has been developed based on data from both the Quiet Technology Demonstrator 2 (QTD2) and the NASA/Boeing Propulsion Airframe Aeroacoustics & Aircraft System Noise (PAA/ASN) full-scale flight tests. The combustor noise prediction model development steps are outlined, and the framework is provided. The most significant findings of this work are how combustor noise has reduced over time and a new method of the correlation of combustor noise. Using the framework, the proposed model has been developed, which reduces the overall combustor noise prediction error on a power-level basis from + ~10-20 dB to +/- 3-5 dB. This will greatly improve the ability to predict both current and future aircraft concepts.

Nomenclature

θ	=	Emission Angle – Relative to the inlet axis
SPL	=	Sound Pressure Level dB – Relative to p_{ref}
C	=	3.52×10^{-7} for “Small Engines” and 8.8×10^{-7} for all others
A*	=	Combustor entrance area (ft^2), re A_e
A_e	=	Engine reference area (ft^2)
$\dot{m}_i^*$	=	Combustor entrance mass flow rate, re $\rho_\infty c_\infty A_e$
T_i^*	=	Combustor entrance total temperature, re T_∞
T_∞	=	Ambient total temperature
T_j^*	=	Combustor exit total temperature, re T_∞
$p_{t,i}^*$	=	Combustor entrance total pressure, re p_∞
H	=	Turbine transfer gain factor
ρ_∞	=	Ambient density, kg/m^3 (slug/ft^3)
c_∞	=	Ambient speed of sound, (ft/s)
p_{ref}	=	Reference pressure (20 μPa)
r_s^*	=	Dimensionless distance from source to observer
M_∞	=	Airplane Mach number
$D(\theta)$	=	Directivity function
$S(f)$	=	Spectral shape function
Π*	=	Acoustic power, re $\rho_\infty c_\infty^3 A_e$
PWL	=	Acoustic power level
A	=	Mass flow multiple linear regression coefficient
B	=	Temperature delta multiple linear regression coefficient
C	=	Constant from multiple linear regression
D	=	Combustor entrance total pressure multiple linear regression coefficient
E	=	Turbine transfer gain factor multiple linear regression coefficient

[1] Senior Research Engineer, Aeroacoustics Branch, AIAA Associate Fellow, Eric.H.Nesbitt@nasa.gov
[2] Research Aerospace Engineer, Aeroacoustics Branch, AIAA Senior Member, Ian.A.Clark@nasa
[3] Senior Research Engineer, Aeroacoustics Branch, AIAA Associate Fellow, Yueping.Guo@nasa.gov
[4] Senior Research Engineer, Aeroacoustics Branch, AIAA Associate Fellow, Russell.H.Thomas@nasa.gov

I. Introduction

Projected growth of the aviation sector highlights the need for significant reduction in aircraft noise around airports while meeting market demands for improved payload, speed, and range performance. NASA's Advanced Air Transport Technology (AATT) Project explores and develops technologies and concepts for improved efficiency and reduced noise generation for fixed-wing subsonic transports [1]. To inform technology development planning and decision making, the AATT Project is continually improving the quality of system noise assessments of current and prospective aircraft. Full-scale flight data are a critical means of improving and validating system noise assessment tools, including the NASA Aircraft NOise Prediction Program (ANOPP).

High-bypass ratio turbofans have emerged as the dominant propulsion system for fixed-wing subsonic transports, exhibiting significant fuel efficiency. Combustion noise, although not the dominant source of noise from high-bypass ratio engines, is very important. This is particularly true in full-scale flight where flight effects reduce jet noise significantly and expose the combustion noise to a greater degree spectrally. Understanding and being able to accurately predict the effects of combustion noise is of particular interest at the lower engine power settings typical of approach, where combustion noise has been shown to contribute more significantly to the overall noise. Better component models allow for more reliable estimation of relative contributions from engine and airframe, which is critical for assessing low-noise airplane concepts.

This paper presents noise data from full-scale flight testing of high-bypass ratio turbofans and use these data to propose an update to the current ANOPP combustor noise prediction [2-3]. The paper will present data from both the Propulsion Airframe Aeroacoustics and Aircraft System Noise (PAA&ASN) Flight Research Test completed in 2020 [4-5], and from the Quiet Technology Demonstrator 2 test completed in 2005 [6]. The installation aspects are important as well, and an understanding of the effects of the combustion noise source versus Propulsion Airframe Aeroacoustics (PAA) aspects is also explored. These effects will be subtracted from the flight test data before the prediction development.

This paper will first go into the history of combustor noise prediction methods, explain the methodology employed in this study, present the results of the investigation and discuss the implications. We will also summarize how the combustor noise data were extracted from the total measured data, how these data compare to the existing ANOPP prediction, and how the improved prediction process compares the measured data.

II. History of Combustor Noise Prediction

A recent, extensive, and well-written review of combustor noise is presented by Tam, et al.[7]. In it they present both direct combustion noise as well indirect (also called entropy) noise. This paper will deal exclusively with direct combustion noise as, at least in the data sets being used here, there is no evidence of entropy noise. This is not to say there is no entropy noise in the full-scale flight test data, it is just to say that at the frequencies and angles where there may be entropy noise, the phased array data indicate the total noise is dominated (to within the dynamic range of the phased array) by noise sources not coming from the primary (core) nozzle.

Direct combustion noise has been studied starting in the early 1970's almost exclusively from analysis of static test data, and as such has been, at least to a significant degree, dependent on the jet noise prediction being used. This is due to the flight effect on jet noise and the need to subtract it out of the data before the combustor noise levels could be understood and studied. This is especially true in the lower frequencies. This is also true (at least in part) for fan noise in the higher frequencies. This work mitigates most of these issues by using full-scale flight test data and by using deconvolved phased array data. The procedure by which this is done will be discussed in detail in section III.

The physical mechanisms that lead to the generation of direct combustion noise are not completely understood or universally accepted [7]. Recently there has been significant advancement in numerical techniques with some limited success [8]. That said, due to the need for quick accurate low-order predictions for use in preliminary and conceptual airplane development, this work focuses on low-order noise modeling and prediction. The two best known low-order models are the Mathews/Rekos model [9] and the GE/SAE model [10]. Hultgren [11] did a detailed comparison of these models as well as a couple of others and recommended the GE/SAE model with an updated turbine attenuation method coming from the Mathews/Rekos model.

Recently McCormick, Hultgren and Mendoza [12] studied the impact of future low-emissions combustor technology on the acoustic scaling laws contained in the above low-order models. Although due to the test setup there was no way to compare the levels on an absolute basis, they concluded that the scaling laws used in either the Mathews/Rekos model or the GE/SAE model worked well (within ~3-5 dB). For these reasons and due to the inability to get the cycle information needed for the Mathews/Rekos attenuation, for this work, we have chosen the GE/SAE model and the attenuation method based on the temperature drop across the turbine as the starting point for this study.

III. Procedure

This study has two advantages over studies using full-scale static tests to extract combustor noise as discussed in the previous section. First this study uses full-scale flight test data, so the flight effect significantly lowers the jet spectral levels and increases the signal to noise ratio of the combustor spectrum. Secondly this study is using deconvolved phased array data that have been matched to the far field data set. The data used as part of the study come from analysis of the phased array data taken during both flight tests previously mentioned. Figure 1 shows an overview of the process used. During the flight testing the data were acquired, and time series based conventional beamforming performed. Deconvolution of the flyover phased array beamform data provided to NASA by Boeing was performed using a version of the CLEAN [13-14] algorithm. Note that a subset of the data have also been deconvolved using DAMAS [15] but with no significant difference in the isolation of combustor noise and a significant increase in processing time.

The beamforming analysis is done on a narrowband basis and then summed to one-third octave bands. A small integration region (“box”) is defined to isolate the combustor noise spectrum, using the assumption that the noise coming from the primary exhaust at frequencies below 1000 Hz is dominated by combustion noise. Then, the total integrated levels over the whole beamform grid are matched to the total ensemble-averaged, de-Dopplerized, 1-ft-lossless data from the far field array to obtain a consistent absolute component data set. The total ensemble-averaged, de-Dopplerized, 1-ft-lossless, far field data are analyzed per the method described in Nesbitt et al. [16].

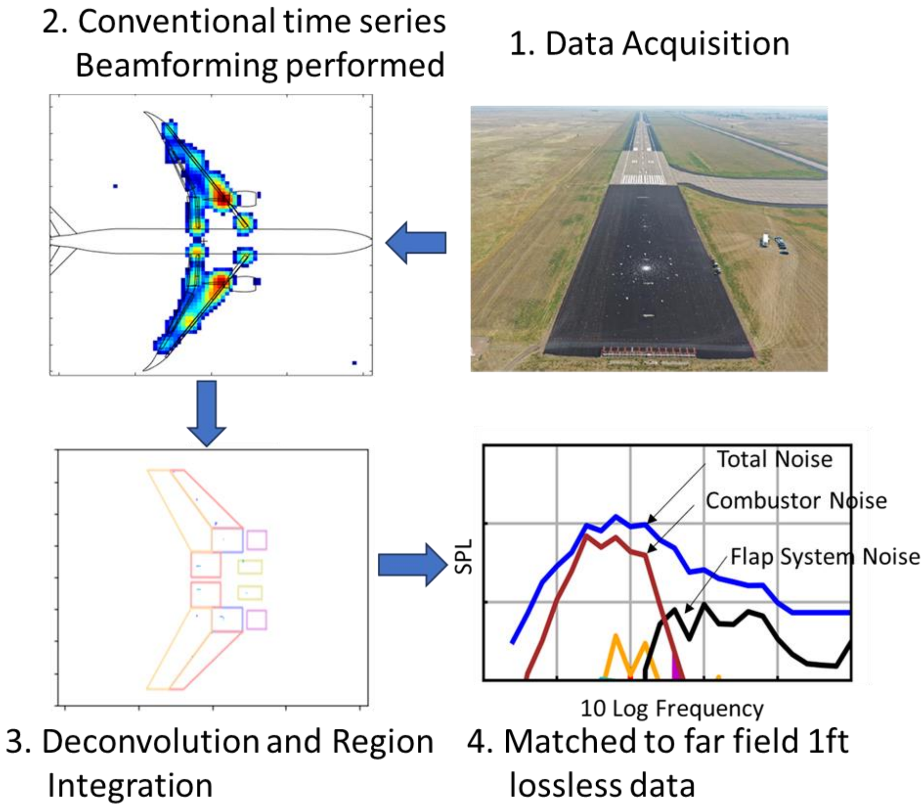

Fig. 1 Phased array results key to separating combustor noise from total airplane noise.

After the combustor noise is isolated, the PAA effects are predicted for the 787 airplane using the Propulsion Airframe Aeroacoustic Scattering code (PAASc) [17]. Figure 2 shows the predicted PAA effects that have been subtracted from the data to get to an isolated engine. Note that these predicted PAA effects are assumed to be the same for the 777 used in QTD2 as it is a twin and also has about the same relative engine position.

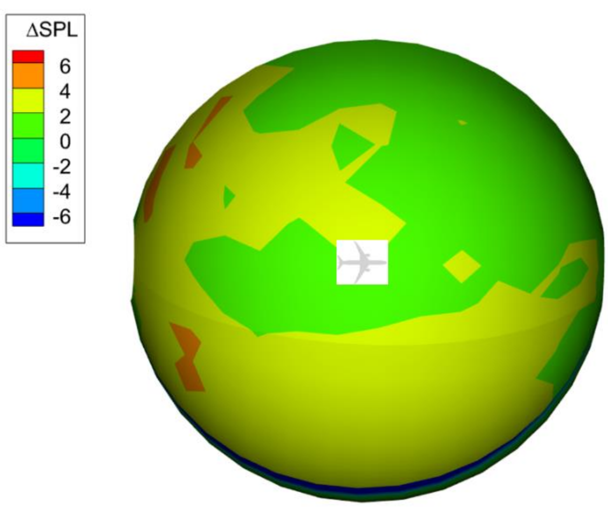

Fig. 2 PAASc predicted PAA deltas shown on a hemisphere.

IV. Power-Level Prediction Development

Once the "isolated engine" has been obtained, it is compared to the existing predictions. The existing prediction equation (from the GE/SAE model, "GECOR" in ANOPP [10]) for the far field mean-square acoustic pressure in a one-third octave band for a gas turbine combustor is:

$$\langle p^2 \rangle^* = \frac{\Pi^* A^*}{4\pi (r_s^*)^2} \frac{D(\theta) S(f)}{(1-M_\infty)^4}, \tag{1}$$

where Π^* is the acoustic power and is defined as:

$$\Pi^* = C \frac{\dot{m}_i^*}{A^*} \left(\frac{T_j^* - T_i^*}{T_i^*} \right)^2 \left(p_{t,i}^* \right)^2 H^2, \tag{2}$$

and the acoustic power level is defined as:

$$PWL = 10 \log_{10} \Pi^* + 10 \log_{10} \frac{\rho_\infty c_\infty^3 A_e A^*}{\Pi_{ref}}. \tag{3}$$

Using the output of Eq. (3), calculating a 1-ft-lossless overall power level, and comparing to the available data sets provides results shown in Fig. 3.

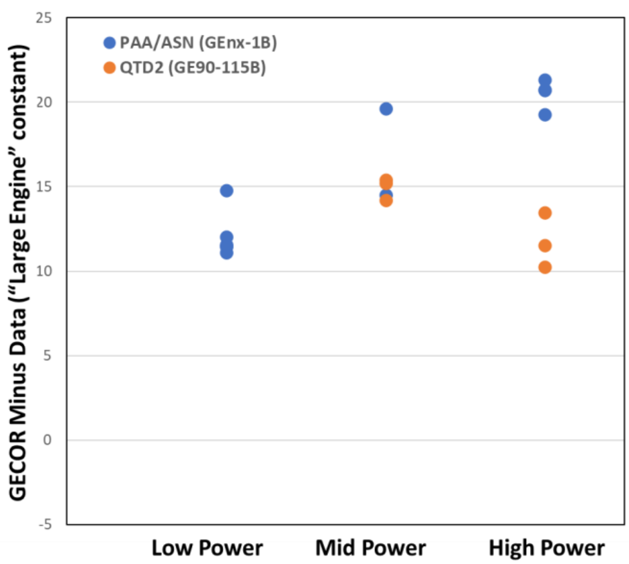

Fig. 3 Overall Power Level difference between flight test results and GECOR.

Examining Fig. 3, three things are clear. First, there is a very significant overprediction of ~10-20 dB. Secondly, even though the scatter of the data is greater at the higher power settings, there is no clear trend where the overprediction would change as a function of power when looking at the overall dataset. Finally, there is a significant difference between the two datasets with the PAA/ASN (GEnx-1B) dataset trending to a much higher overprediction than the QTD2 (GE90-115B) dataset. To study this in greater detail a modification to Eq. (2-3) is proposed. The acoustic power level from Eqs. 2-3 can be rewritten as:

$$PWL = A\log_{10}\frac{\dot{m}_i^*}{A^*} + B\log_{10}\left(\frac{T_j^*-T_i^*}{T_i^*}\right) + D\log_{10}\left(p_{t,i}^*\right) + E\log_{10}H + C + 10\log_{10}\frac{\rho_\infty c_\infty^3 A_e A^*}{\Pi_{ref}}. \quad (4)$$

The coefficients A, B, C, D, and E can now be determined from a multiple linear regression using the available datasets and minimizing the prediction difference to the data. After exploring a few different methods for the measurement of the prediction difference, the coefficient of determination (R^2) was used. Also, after consideration only the values of B, C, and D were optimized, and the values of A and E were left unchanged. A is the exponent on the mass flow and including it into the optimization made its value increase to close the gap between the engines. That said, this did not seem reasonable and for similar reasons the exponent on the attenuation through the turbine was left unchanged. An objective function was then created to maximize R-squared value, then the optimization was done using the evolution optimization function within SciPy [18] with limits set to keep the values of the exponents reasonable. Figure 4 shows the output of the optimization.

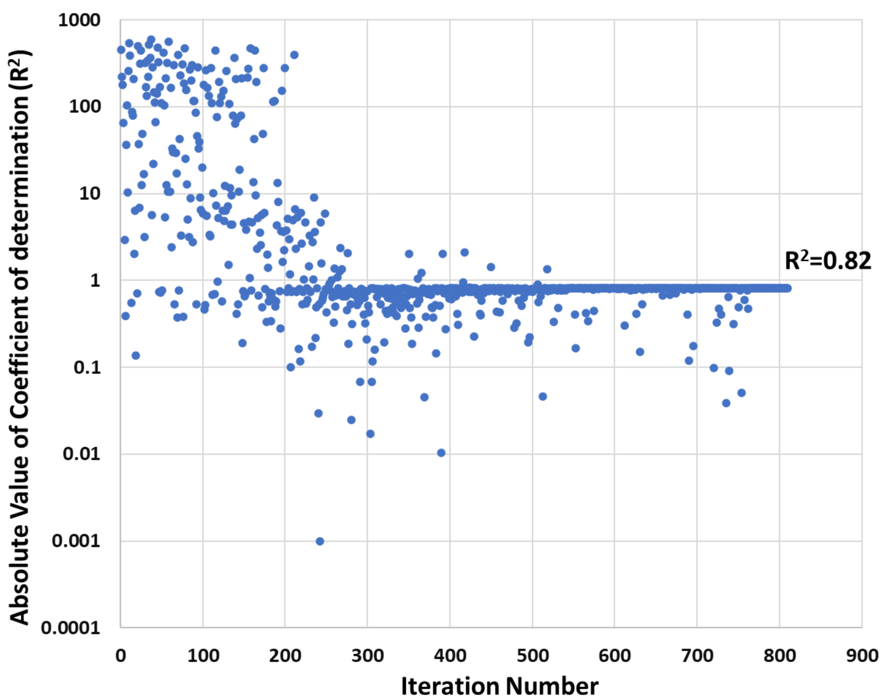

Fig. 4 Output of the evolution optimization for R^2.

As Fig. 4 shows the optimization converged after 800+ interations and came to an optimum R^2 value of 0.82. Note the large values (>1) are negative since Fig. 4 is plotted on a log scale to better see the converance and to this required an absolute value be applied. It should also be noted that although the values of the exponents output from this optimization cannot be shared at this time due to proprietary issues, the change generally goes in the direction a reduced slope as a function of power as the study by McCormick, et. al. [12] would indicate.

Note that the significant difference between the datasets has been explored and it has been concluded that most of the difference is likely due to the two combustors in question being designed ~20 years apart and with different technologies and the difference cannot be completely accounted for without the use of information not available to include in this low-order model. That said, as Fig. 5 shows the output of the optimization results in an overall reduction in scatter as well as some collapse between the datasets.

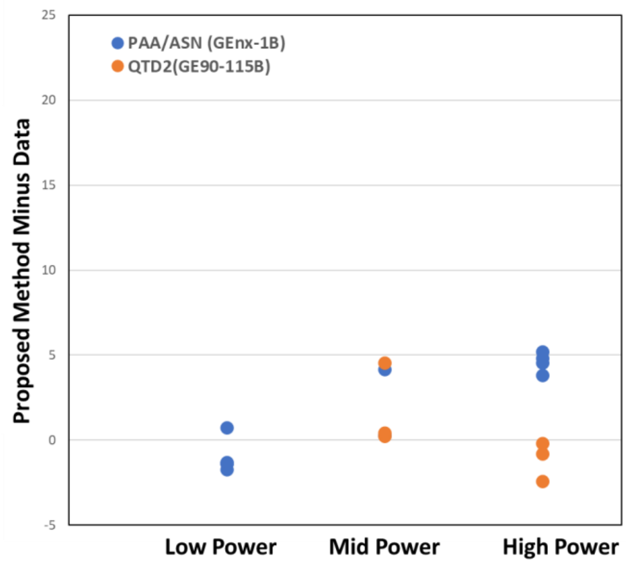

Fig. 5 Overall power level difference between flight test results and new method.

Figure 5 also shows the different between the datasets and the prediction is now on the order of 3-5 dB, which is in line with the original development results.

V. Directivity Function Development

The directivity function is the next thing to consider. The development of the directivity function is illustrated in Fig. 6.

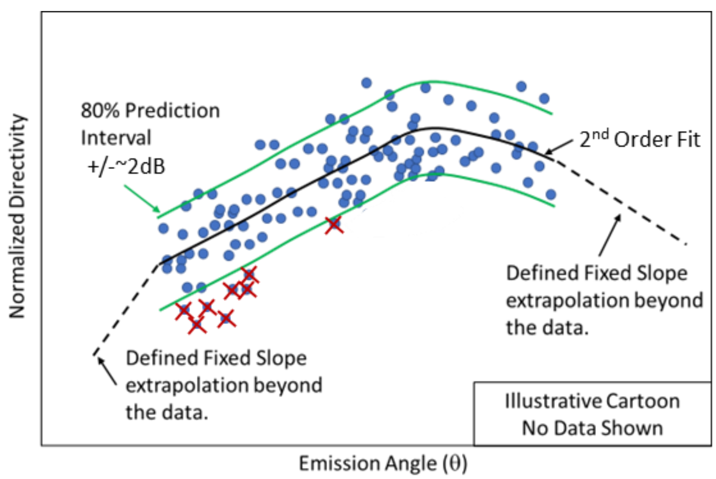

Fig. 6 Directivity function development.

The normalized directivity data were plotted as a function of emission angle (θ) and a 2nd order least squares fit was performed. When this was done it was noted that a significant number of data points fell below the 80% prediction interval in the forward arc and that these data points were significantly biasing the curve to be low in the forward arc. Since the component separation at these angles is the most uncertain these data points were excluded from the final curve fit. The final curve and how it compares to the GE/SAE model ("GECOR") is shown in Fig. 7.

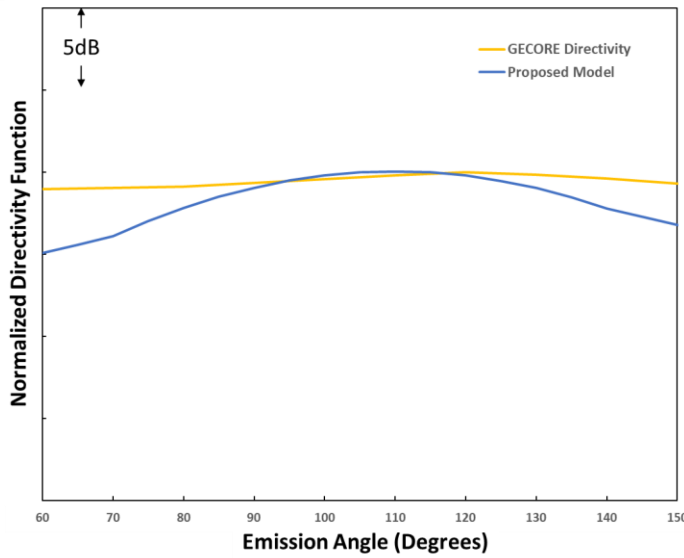

Fig. 7 Directive shape of the proposed model versus GECOR.

As Fig. 7 shows the new proposed model's directivity peaks forward and rolls off faster than the GE/SAE model. The proposed directivity function peaks at ~110 degrees whereas the GE/SAE model peaks at 120. The new proposed model is also 5 dB down from the peak by 60 degrees compared to ~1 dB for the GE/SAE Model. Although the reasons for this are not completely understood, it is noted that the proposed model has been created using full-scale flight test data and therefore has a lower shear layer strength in the secondary/ambient shear layer than the data used in all previous models. Finally, this update to the directivity function is a significant change that is being made with the proposed model and will result in combustor noise being more dominant close to overhead and less dominant at forward and aft angles that have been previously predicted with the GE/SAE model.

VI. Spectral Function Development

The spectral shape is the last remaining issue to explore. Fig. 8 shows a comparison of the spectral shape from the datasets and the GE/SAE (GECOR) spectral shape function.

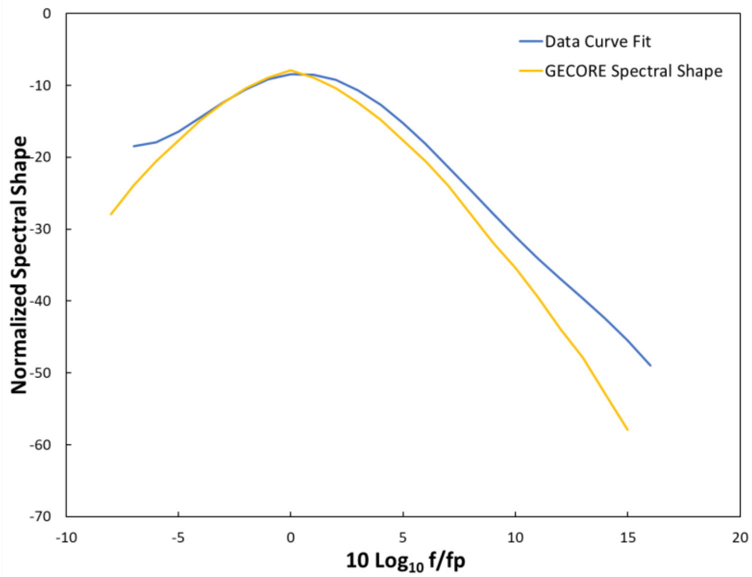

Fig. 8 Spectral shape function of GECORE versus data.

The figure shows that the spectral shape function matches the data to within ± 2 dB over a frequency range three octaves below to two octaves above the spectral peak. Given that the technique for identifying the combustor noise from the datasets has significant uncertainty at both low and high frequencies, this is a remarkably good comparison. For this reason, the proposed model does not update the spectral shape function of the GE/SAE model.

VII. Results compared to Independent Data Set

This section compares the predicted levels using the proposed model against data provided by the Raytheon Corporation and shown by McCormick, et al. [12]. Although, as noted previously, the test setup precludes any direct level comparisons, McCormick, et al. [12] developed a level that is directly proportional to a power level so the correlation as a function of power can be examined. Figure 9 shows the "N" combustor data reported in Fig. 14a of reference [12] versus the new method with a constant added to get the levels to be similar.

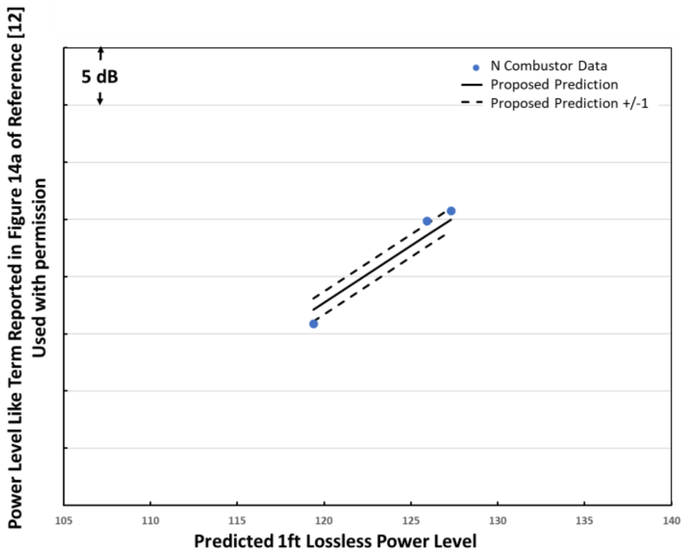

Fig. 9 New method versus N combustor data.

The figure shows the proposed prediction has very much the same slope as a function of power as the data are generally within +/1 dB. This shows that for a completely independent data set from a different manufacturer the new methods scaling laws are giving results that are within the data scatter of the data used to develop the model. It should be noted that the above comparison is shown only for the N combustor data and the N+3 combustor data are not shown due not having access to the necessary engine cycle information. The N+3 data would likely be a worse comparison due to the N+3 data shown in [12] having a somewhat larger slope as a function of engine power. That said, this still gives confidence that the proposed model's slope and the derived exponents are likely transferable and can be used for situations with combustors from other manufacturers.

VIII. Summary/Conclusions

This is the first time full-scale large turbofan flight test data have been used in the development of a combustor noise prediction process for eventual inclusion in the NASA ANOPP prediction process. The process for analyzing and predicting combustor noise from flight test results has been defined and used to compare to current predictions. The overprediction on a power-level basis is very significant and approximately 10 to 20 dB. The proposed improved method largely eliminates this overprediction while also improving the overall collapse of the data. The comparisons to the independent data taken by McCormick, et al [12] also show an improved correlation and although it is not possible to validate the absolute levels, they show the new method scaling laws do better at predicting the effects of engine power settings even across combustors from different OEMs.

The implications of this work are significant. It is emphasized that the proposed model has been created using research-quality data from highly relevant full-scale flight tests on state-of-the-art aircraft with modern engines. It is anticipated the new prediction method will be shown to exhibit strongly improved characteristics relative to prior system-level combustor noise prediction methods. It is also expected that the model presented in this work represents a significant improvement in the ability of NASA to predict noise for both current in-service aircraft and future aircraft concepts.

Acknowledgments

Funding for this research by the NASA Advanced Air Transport Technology Project is gratefully acknowledged. The exceptional efforts of The Boeing Company and the Boeing ecoDemonstrator Program are gratefully acknowledged in the execution of the tests and the delivery of the data used in this study. The authors would also like the acknowledge and thank the authors of Reference [12] for agreeing to give access to the cycle data necessary to do the predictions and the permission to make the independent data set comparisons.

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