Aeroacoustic Characterization of Optimum Hovering Rotors using Artificial Neural Networks

Christopher S. Thurman
Research Aerospace Engineer
NASA Langley Research Center
Hampton, VA, USA

Nikolas S. Zawodny
Research Aerospace Engineer
NASA Langley Research Center
Hampton, VA, USA

ABSTRACT

This work illustrates the use of artificial neural network modeling in the aerodynamic and aeroacoustic characterization of optimum hovering rotors over a broad range of design and operating conditions. Design of Experiments was used to create input feature spaces over eight input factors: the number of rotor blades, rotor radius, rotor rotation rate, design thrust condition, collective pitch, airfoil camber, the location of maximum camber, and the airfoil thickness. A low-fidelity tool chain was then used at the discrete data points defined by the designed input feature spaces to analytically design optimum hovering rotors and simulate aerodynamic and aeroacoustic quantities. This allowed for the generation of data sets over which to train and test the artificial neural network prediction models. Prediction models were trained over the data sets for the actual thrust generated by the rotor, power loading, tonal thickness and loading noise at the fundamental blade passage frequency, and broadband self-noise at seventeen one-third octave bands between 1 kHz and 40 kHz. These prediction models were validated by testing over data previously unseen by the models to quantify their capability for generalization to new data within the design feature space. The models were then used to study the effect each input feature had on the aeroacoustics and aerodynamics of optimum hovering rotors, and physical insights were gained to further explain the effect of each input. This characterization study showed that tonal noise and power loading were most sensitive to the number of rotor blades and the rotor rotation rate and that broadband noise was most sensitive to collective pitch and the design thrust condition.

NOTATION

\begin{align*}
c(r) & \quad \text{Rotor chord length distribution, inches} \\
C_T & \quad \text{Thrust coefficient,} \quad \frac{F}{\rho A \Omega^2} \\
M & \quad \text{Airfoil maximum camber, percentage of chord} \\
N & \quad \text{Airfoil location of maximum camber, percentage of chord} \\
N_b & \quad \text{Number of rotor blades} \\
OASPL & \quad \text{Overall sound pressure level, dB} \\
PL & \quad \text{Power Loading, lb/HP} \\
P_T & \quad \text{Total (i.e., induced and profile) power, HP} \\
R & \quad \text{Rotor tip radius, inches} \\
r & \quad \text{Normalized span location,} \quad \frac{\bar{x}}{R} \\
SPL & \quad \text{Sound pressure level, dB} \\
T_{\text{design}} & \quad \text{Design thrust condition, lb} \\
T_{\text{pred}} & \quad \text{Predicted rotor thrust, lb} \\
XX & \quad \text{Airfoil thickness, percentage of chord} \\
\alpha(r) & \quad \text{Angle of attack distribution, deg} \\
\alpha_0 & \quad \text{Airfoil zero lift angle of attack, rad} \\
\Omega & \quad \text{Rotor rotational rate, revolutions per minute (RPM)} \\
\phi(r) & \quad \text{Inflow angle distribution, deg} \\
\sigma(r) & \quad \text{Rotor solidity distribution,} \quad \frac{N_b c(r)}{\pi R} \\
\Theta_{\text{obs}} & \quad \text{Observer angle relative to rotor plane, deg} \\
\theta_{tw}(r) & \quad \text{Rotor twist distribution, deg} \\
\theta_0 & \quad \text{Collective pitch, deg.}
\end{align*}

INTRODUCTION

Demand for small unmanned aerial systems (sUAS) has increased due to their potential for missions such as package delivery and aerial surveillance. When comparing sUAS to traditional helicopters, the relative importance of noise generating mechanisms differs. For example, it has been shown that the stochastic (i.e., broadband) portion of the noise emanating from sUAS vehicles lies in the most perceptible range of human audibility and is a dominant noise source when compared to the deterministic (i.e., tonal) noise, which dominates for traditional helicopters (Refs. 1 and 2).

Many tools exist for predicting both tonal and broadband noise (Refs. 1–4). For modeling tonal noise, a wide range of multifidelity tools exist: panel methods, blade element momentum theory (BEMT), comprehensive analysis codes, traditional Navier-Stokes solvers, and scale-resolving flow simulations. Each of these tools is used to predict unsteady aerodynamic forces. The resulting acoustic pressures are propagated to arbitrary observer locations using an implementation of the Ffowcs Williams and Hawkings (FW-H) equation. Similar approaches have been used to predict broadband noise.
The purpose of the present research was to develop aero-
dynamic and aeroacoustic prediction models using machine-
learning-based approaches to characterize representative
sUAS rotors in hover. Specifically, this work focused on rigid
optimum hovering rotors. A four-step approach shown in Fig.
1 was adopted in this work.

**TECHNICAL APPROACH**

**Design of Experiments**

DoE is a process used for planning an experiment so that
appropriate data can be collected and analyzed by statistical
methods, resulting in valid and objective conclusions (Ref. 7).
DoE is typically used in systems comprised of multiple inputs
when a nonlinear functional relationship between the quanti-
ties of interest, such as force and moment coefficients, and the
regressors, or inputs, and their interactions is required. DoE
can be broken up into two categories: classical and modern.
A comprehensive study of both categories of DoE was per-
formed by the author in Ref. 8, which showed the superiority
of modern DoE in the context of computer-based experiments,
such as those performed in this work.

Modern DoE was used in this work to design a feature space
consisting of the following inputs for the aerodynamic predic-
tion models: \( N_b, R, \Omega, T_{\text{design}}, \theta_b, M, N, \) and \( XX \). The same
input features were used for the aeroacoustic models; how-
ever, with the inclusion of the angle between the acoustic ob-
server location and the center of the rotor, \( \Theta_{\text{obs}} \). There were
seven discrete observer locations prescribed along an arc lo-
cated 1.896 m away from the center of the rotor, similar to
the observer array used in Ref. 3. The range and type of each
input feature are shown in Table 1.

<table>
<thead>
<tr>
<th>Input Feature</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>( N_b ) *</td>
<td>2, 3, 4</td>
</tr>
<tr>
<td>( R )</td>
<td>6 in - 8 in</td>
</tr>
<tr>
<td>( \Omega )</td>
<td>3500 RPM - 6000 RPM</td>
</tr>
<tr>
<td>( T_{\text{design}} )</td>
<td>1.5 lb - 3.0 lb</td>
</tr>
<tr>
<td>( \theta_b )</td>
<td>-5° - +5°</td>
</tr>
<tr>
<td>( M )</td>
<td>0% - 9%</td>
</tr>
<tr>
<td>( N )</td>
<td>20% - 50%</td>
</tr>
<tr>
<td>( XX )</td>
<td>6% - 15%</td>
</tr>
<tr>
<td>( \Theta_{\text{obs}} ) *</td>
<td>-45°, -30°, -10°, 0°, +10°, +30°, +45°</td>
</tr>
</tbody>
</table>

Table 1: Input feature space. (* indicates categorical factors.
All other factors are continuous.)

Since machine learning prediction modeling is an interpo-
lation problem, it is imperative to spread the input feature
design points uniformly throughout the feature space by us-
using various alphabetically optimal designs or space-filling de-
signs. Alphabetic optimality refers to placing design points so
that some optimality criterion, such as prediction variance or
regressor screening capability, is satisfied. Space-filling de-
signs, such as the Uniform Design (UD), Latin Hyper-Cube

Figure 1: Block diagram representation of technical approach
where \( x_i \) is the \( i \)th input feature, \( y_j \) is the \( j \)th result using the
low-fidelity tools, and \( f_j \) is the \( j \)th machine learning predic-
tion model.

The first step entailed the use of modern Design of Experi-
ments (DoE) to create an input feature space or design space
consisting of discrete combinations of input variable values.
The input feature space consisted of various airfoil and rotor
geometric parameters as well as flight conditions, which were
thought to encapsulate much of the sUAS region of operabil-
ity. Preexisting low-fidelity tools were then used to predict
various aerodynamic and aeroacoustic quantities at the design
points prescribed by the feature space. Once these data were
generated, machine learning was used to develop prediction
models to accurately and quickly predict various aerodynamic
and aeroacoustic quantities of particular interest to rotorcraft.
Lastly, and most importantly, these prediction models were
used in a characterization effort to study the effects of each
input feature on both the aerodynamics and aeroacoustic tonal
and broadband noise.

The purpose of the present research was to develop aero-
dynamic and aeroacoustic prediction models using machine-
learning-based approaches to characterize representative
sUAS rotors in hover. Specifically, this work focused on rigid
optimum hovering rotors. A four-step approach shown in Fig.
1 was adopted in this work.

![Diagram](image_url)
Design, Sphere-Pack ing Design, etc., spread the design points evenly throughout the region of experimentation, adhering to some measure of uniformity determined by the design being used (Ref. 9). The purpose of this uniform sampling is to acquire data in a manner that represents the entire experimental domain while minimizing the difference of the overall mean between the prediction model and the experimental data (Ref. 10).

A space-filling UD was selected for this work, which minimized the centered $L_2$ discrepancy between the design points and a theoretical distribution (Ref. 11). Since $N_b$ is a discrete (i.e., categorical) factor, three designs were created, one at each discrete value of $N_b$, for a total of 144 design points. The ensemble of these designs was used as the training set for the machine learning prediction models. It is common in machine learning to split the dataset into training and testing data; however, when using DoE, this data split may produce bias toward specific regions of the design space. For example, if all split training data are located in a particular quadrant of the design space, there will be inadequate coverage over the entirety of the design space to train the prediction model. For this reason, a separate design space was created over the same input feature space for the test data, which contained 48 points. The low-fidelity tools discussed in the subsequent section were then used to simulate the prescribed design points, and machine learning was used to create aerodynamic and aeroacoustic prediction models with functional relationships to the defined input features.

Low-Fidelity Tools

Throughout this work, various low-fidelity tools were utilized to allow for rotor designs comprised of the NACA four-digit airfoil geometric parameters: the camber, $M$, location of maximum camber, $N$, and thickness, $XX$, as well as characteristic rotor properties such as the rotor radius, $R$, number of blades, $N_b$, design thrust condition, $T_{design}$, collective pitch, $\theta_0$, and rotor rotation rate, $\Omega$. The aerodynamic prediction tool, XFOIL, was used to calculate a zero lift angle of attack, $\alpha_0$, based upon the airfoil properties. These properties were used in conjunction with the rotor properties and Eq. 1 from Ref. 12 to calculate the rotor blade twist distribution of an optimum hovering rotor with a tip chord length, $c_{tip}$, of 0.5 in:

$$\theta_{tw}(r) = \frac{1}{r} \left( \frac{4CT_{design}}{5.733\sigma(r)} + \sqrt{\frac{C_{r,design}}{2}} \right) - \alpha_0, \quad (1)$$

where $r$ is the normalized span location and $C_{r,design}$ is the thrust coefficient calculated using $T_{design}$.

An optimum hovering rotor can be defined as one that has both minimal induced power requirements and minimal profile power requirements. Equation 1 is such that the rotor induces uniform inflow, satisfying the induced power requirement. To satisfy the profile power requirement, the chord distribution of the rotor, $c(r)$, follows that of Eq. 2 from Ref. 12, which allows for each radial station to operate at an optimal lift to drag ratio:

$$c(r) = \frac{c_{tip}}{r}, \quad (2)$$

where $r$ is the normalized span location.

Since this optimum chord distribution is generally not physically realizable, a linear taper ratio of 2.5 to 1 was selected for this work. This linear taper ratio was thought to best replicate the taper of an optimum hovering rotor over the outboard 25% span of the rotor, as shown in Fig. 2. The chord dimension in this plot has not been nondimensionalized since $c(r)$ is constant for all designed rotors.

![Rotor Chord Distribution](image)

Figure 2: Comparison of 2.5 to 1 linear taper ratio to the taper ratio of an optimum hovering rotor.

ANOPP’s Propeller Analysis System (PAS) (Ref. 13) was used to calculate the aerodynamic thrust generated by the rotor, $T_{pred}$, and the total (i.e., induced and profile) power, $P_T$, needed by the rotor, tonal (i.e., thickness and loading) noise on a dB basis at the fundamental blade passage frequency (BPF), and finally, various rotor inflow parameters, such as the induced inflow angle distribution, $\phi(r)$, and angle of attack distribution, $\alpha(r)$. These inflow parameters were then used within ANOPP’s 2’s Self-Noise Internal Functional Module (ASNIFM) (Ref. 14) to calculate the broadband self-noise, also on a dB basis, ANOPP’s PAS and ASNIFM, which is an implementation of the semiempirical prediction methodology devised by Brooks et al. in Ref. 6, were selected based upon their promising prediction accuracy. These low-fidelity tools allowed for the generation of aerodynamic and aeroacoustic data sets, which were vital to the machine learning prediction modeling approach used in this research.

Machine Learning Methodology

Artificial Neural Networks (ANNs) were chosen as the prediction models used to fit the data within the design space; more specifically, Multilayer Perceptrons (MLP) were used. The MLP aims to replicate the architecture of the neurons in the human brain, set up in layers as shown in Fig. 3. Each “hidden” layer consists of a number of activation functions, or neurons, aligned in parallel. All of the neurons of a particular layer are activated in unison, with different multiplicative
weights along the connections between neurons, inputs, and outputs.

\[
\begin{align*}
\text{Input Layer} & \rightarrow \text{Hidden Layers} & \rightarrow \text{Output Layer} \\
X_i & \rightarrow \
onumber \theta_{ij} \rightarrow \nonumber \Sigma_j \rightarrow f_j(x_{i1}, x_{i2}, \ldots, x_{in}) \\
Y & \rightarrow \nonumber \nonumber \nonumber
\end{align*}
\]

Figure 3: Generic ANN representation where \(x_i\) is the \(i\)th input feature, \(\omega\) and \(\mu\) are multiplicative weights, \(\Sigma\) is a summation operator, \(\gamma\) is the activation function evaluated over the summed inputs multiplied by their respective weights, \(\theta\) are the hidden layers, and \(f_j\) is the \(j\)th ANN prediction model.

The machine learning procedures used throughout this work were performed using Google's TensorFlow platform (Ref. 15). The MLP architecture used for all prediction models contained two hidden layers consisting of 100 exponential linear units (ELU) with a linear activation function in the output layer. These ELU were selected over the commonly used rectified linear unit (ReLU) as they are less prone to vanishing gradients and have better overall convergence trends with more accurate results (Ref. 16). The number and type of activation functions used are heuristically determined. It should be noted that ANNs of different architectures and consisting of different activation functions were investigated; however, those mentioned previously were determined to perform optimally for this work.

It was first imperative to rescale each input feature listed in Table 1 to a common basis to eliminate any bias in the optimization procedure of the cost function. To achieve a common basis, each feature was scaled such that it had a mean of zero and a variance of one. The input layer contained values of these scaled inputs at each discrete point in the feature space, which were then passed through the MLP over 1250 epochs, or cycles through the training data. The multiplicative weights along the connections were modified after each epoch until the specified cost function, in our case, the mean absolute error (MAE), was sufficiently minimized using the Adam optimization algorithm (Ref. 17).

Two types of regularization were used on each of the hidden layers: \(L_2\) regularization and a 20% dropout. The \(L_2\) regularization acted to constrain the multiplicative weights. The 20% dropout randomly eliminated 20% of the activation functions in each hidden layer during the training procedure at each epoch (Ref. 18). Regularization is vital to any machine learning procedure in that it aids in reducing the prediction model’s bias toward the training data and aids in promoting better generalization to new data. An early stopping criterion was also imposed on the learning procedure to further reduce the possibility of overfitting. A 10-fold cross-validation method was used where the training data were randomly split into ten equally sized partitions. Ten prediction models were then fit over a different set of nine partitions, using the last partition for accuracy evaluation at each epoch during training. These ten models were then evaluated over the test data set, which had not been previously seen by the models, and the model with the highest prediction accuracy was retained.

Because \(N_b\) was a categorical factor, one-hot encoding was used, which treated this input feature as three binary inputs. For example, for a two-bladed rotor, the input correspondent to a two-bladed rotor would hold a value of one and the other two inputs correspondent to three- and four-bladed rotors, respectively, would hold values of zero. For the aeroacoustic prediction models, one-hot encoding was also used for \(\Theta_{\text{obs}}\). Since the data were acquired over all seven observer angles for each design point in the feature space, all design points were replicated for each observer location and their ordering was randomized prior to the training procedure.

Since this work focused on aerodynamic and aeroacoustic characterization, two prediction models were produced for aerodynamics, one for \(T_{\text{pred}}\), and one for power loading (PL), or the ratio of \(T_{\text{pred}}\) to \(P_f\). Only the prediction model for PL was used for aerodynamic characterization throughout this work; however, generating a prediction model for \(T_{\text{pred}}\) allows for the future calculation of aerodynamic quantities of particular importance to rotorcraft, such as the induced power, profile power, and torque. It should be noted here that \(T_{\text{design}}\) was used solely for the design of the rotor and \(T_{\text{pred}}\) includes additional aerodynamic effects caused by the airfoil geometry and \(\theta_0\). Two models were created for the tonal noise at the fundamental BPF, one for the thickness noise and one for the loading noise, both on an overall sound pressure level (OASPL) basis. For the broadband noise, separate prediction models were created for each one-third octave band between 1 kHz and 40 kHz, totaling seventeen broadband noise prediction models.

RESULTS

Prediction Model Performance and Validation

An accuracy score produced using Eq. 3 was calculated over the test data and is shown in Table 2. For brevity, these quantities were averaged over the seventeen prediction models for the broadband one-third octaves:

\[
\text{Prediction Accuracy} = 100 \times \left(1 - \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - f_i}{y_i} \right| \right),
\]

where \(n\) is the number of test data values, \(y_i\) is the test data value, and \(f_i\) is the predicted value.

Table 2 shows that the prediction accuracy values are above 95% for all aeroacoustic models (e.g., OASPL$_{\text{thickness}}$, OASPL$_{\text{loading}}$, and SPL$_{1/3\text{broadband}}$). This signifies that these
models have adequately learned the underlying functional relationships between the inputs and outputs and that they generalize exceptionally well to new data within the feature space. Both aerodynamic models (e.g., PL and $T_{\text{pred}}$) have prediction accuracy values of approximately 85%, which is sufficient for the purposes of this study. Since characterization is the goal of this effort, the aerodynamic models are used to assess general behavioral trends of aerodynamic performance with favorable aeroacoustic behavior; therefore, prediction accuracy scores above 80% are thought to be adequate for this work.

Table 2: Prediction model fit summary.

<table>
<thead>
<tr>
<th>Prediction Model</th>
<th>Prediction Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>$PL$</td>
<td>85.89%</td>
</tr>
<tr>
<td>$T_{\text{pred}}$</td>
<td>85.62%</td>
</tr>
<tr>
<td>OASPL-thickness</td>
<td>98.16%</td>
</tr>
<tr>
<td>OASPL-loading</td>
<td>97.09%</td>
</tr>
<tr>
<td>SPL/1/broadband</td>
<td>95.79%</td>
</tr>
</tbody>
</table>

As a further validation, an arbitrary design point within the feature space was selected to compare predicted results to results generated using the low-fidelity tools. The aerodynamic results from the low-fidelity tools were $T_{\text{pred}} = 3.43$ lb and $PL = 16.47$ lb/HP and the results predicted using the ANNs were $T_{\text{pred}} = 3.22$ lb and $PL = 16.73$ lb/HP. The OASPL of the broadband noise between 1 kHz and 40 kHz was calculated and Fig. 4 shows the comparison between the ANN predicted results and the results generated from the low-fidelity tools for the thickness, loading, and broadband noise at all observer locations. The agreement between the results from the ANN prediction models and the results generated using the low-fidelity tools is consistent with the high prediction accuracy values shown in Table 2.

Aeroacoustic Rotor Characterization

To compare the effects of each input feature on the rotor acoustics, the ANNs were used to predict acoustic directivities of the tonal thickness, tonal loading, and broadband OASPL at the maximum and minimum values of each input feature defined in Table 1. All other input features were maintained at their mean values. These acoustic directivity plots were generated using the same scaling to allow for a more direct visual comparison. Predictions using the mean values for all input features were also plotted to further illustrate the variation in tonal and broadband noise caused by each input feature. Additionally, Eq. 1 and ANOPP’s PAS were used to develop plots for the twist distribution, $\theta_{tw}(r)$, inflow angle distribution, $\phi(r)$, and angle of attack distribution, $\alpha(r)$, at the maximum, minimum, and mean values of each input feature. This was done to provide physical insight as to why the input features affect the rotor acoustics. Separate plots have been created for each input feature in Figs. 5–9, which show the aerodynamic and aeroacoustic quantities. Examining subfigures (a) and (b) in Figs. 5–9, it can be seen that for an optimum hovering rotor, tonal noise is dominated by the loading noise, implying that input features that produce greater variations to the loading noise are highly influential to the entire tonal noise signature.

It can also be ascertained by comparing Figs. 5–9 that the value of $N_b$ has the greatest effect on tonal loading noise with decreasing values of $N_b$ causing an increase in BPF amplitude. Since $\theta_{tw}(r)$ from Eq. 1 has functional dependence on $C_{\text{design}}$ and $\sigma$, decreasing the number of rotor blades while maintaining the same value of $C_{\text{design}}$ would decrease the value of $\sigma$. Figure 5 shows that decreasing the value of $N_b$ causes an increase in the distributions of $\theta_{tw}(r)$ and $\alpha(r)$, resulting in increased tonal thickness noise, loading noise, and broadband noise. Similarly, Fig. 6 shows that increasing the value of $R$ resulted in a decrease in the value of $\sigma$ and a decrease in the distributions of $\theta_{tw}(r)$, $\phi(r)$, and $\alpha(r)$. Increasing the value of $R$ would also result in an increased tip Mach number for a fixed value of $\Omega$. The combination of these opposing geometric effects caused by increasing the value of $R$ resulted in a slight increase to tonal noise and a decrease in broadband noise. However, both the tonal loading and broadband noise are less sensitive to $R$ than to $N_b$. Although $\theta_{tw}(r)$, $\alpha(r)$, and the tonal thickness noise vary similarly with increasing values of $R$ and decreasing values of $N_b$, the decrease in $\phi(r)$ caused by increasing the value of $R$ was thought to alleviate the effect of the increased tip Mach number on the tonal loading noise, explaining why variations of $N_b$ have a greater effect on tonal loading noise than variations of $R$. In summary, the value of $\sigma$ has a dominant effect on the tonal noise with $N_b$ having a greater effect when compared to $R$, regardless of the similar dependence of $\sigma$ on both of these input features.
Figure 5: Blade number effect on tonal noise directivity, broadband noise directivity, twist distribution, inflow angle distribution, and angle of attack distribution. $R = 7$ in, $T_{\text{design}} = 2.25$ lb, $\Omega = 4750$ RPM, $M = 4.5\%$, $N = 35\%$, $XX = 10.5\%$, and $\theta_0 = 0^\circ$.

Figure 6: Radius effect on tonal noise directivity, broadband noise directivity, twist distribution, inflow angle distribution, and angle of attack distribution. $N_b = 3$, $T_{\text{design}} = 2.25$ lb, $\Omega = 4750$ RPM, $M = 4.5\%$, $N = 35\%$, $XX = 10.5\%$, and $\theta_0 = 0^\circ$.

Figure 7 shows that the second most significant input feature to the tonal noise is $\Omega$. Although increasing the value of $\Omega$ decreases the distributions of $\theta_{\text{in}}(r)$, $\phi(r)$, and $\alpha(r)$ while increasing the tip Mach number, its effect on the tonal thickness noise is much more pronounced than for variations of $N_b$ and $R$, elucidating the high significance of this input feature on the acoustic results. The effect of varying $\Omega$ on the tonal loading noise, shown in Fig. 7b, can also be seen to have a greater significance than for variations of $R$ and lesser significance than for variations of $N_b$.

Variations of $\theta_0$ affect the tonal loading noise in a similar fashion to variations of $\Omega$ with negligible change to the tonal thickness noise for changes in the value of $\theta_0$. Figure 8b shows large variations in the tonal loading noise, thought to be caused by the increasing distributions of $\theta_{\text{in}}(r)$, $\phi(r)$, and $\alpha(r)$. Figure 8c also shows that variations of $\theta_0$ have the
tonal loading noise.

Broadband noise.

Inflow angle distribution.

Rotor Rotation Rate Effect on Tonal Thickness Noise Directivity

Rotor Rotation Rate Effect on Tonal Loading Noise Directivity

Rotor Rotation Rate Effect on Broadband Noise Directivity

Figure 7: Rotor rotation rate effect on tonal noise directivity, broadband noise directivity, twist distribution, inflow angle distribution, and angle of attack distribution. 

(1) Tonal thickness noise.

(2) Tonal loading noise.

(3) Broadband noise.

(4) Twist distribution.

(5) Inflow angle distribution.

(6) Angle of attack distribution.

greatest effect on the broadband self-noise. The increased distributions of $\phi(r)$ and $\alpha(r)$ were believed to give rise to the broadband self-noise mechanism, trailing edge separation noise (Ref. 6), which could explain the large sensitivity of broadband noise to variations of $\theta_0$. Increasing the value of $T_{design}$ was seen to have an almost identical trend on the aerodynamics and aeroacoustics as increasing the value of $\theta_0$, so plots for $T_{design}$ were omitted.

Increases in the value of $M$ serve to increase $\alpha_0$, which would increase the thrust generated by the rotor while reducing the distribution of $\alpha(r)$ for a given thrust value. Figure 9 shows that increasing the value of $M$ decreases the distributions of both $\theta_{tw}(r)$ and $\alpha(r)$, resulting in a slight increase in tonal loading noise and a minimal decrease in broadband noise. Increasing $XX$ was seen to have no impact on the distributions of $\theta_{tw}(r)$ and $\phi(r)$ with very negligible effects on the distribution of $\alpha(r)$. Increasing the value of $XX$ increased the tonal thickness noise but resulted in an almost identical trend in the tonal loading noise and broadband noise as for increasing the value of $M$, so these plots were excluded. Lastly, variations of $N$ had a negligible effect on all aerodynamic and aeroacoustic quantities so plots for $N$ were also excluded for brevity.

Table 3 shows $PL$ results at the previously defined maximum and minimum values for each input feature. For reference, $PL = 17.55$ lb/HP is the predicted value with all input features retained at their mean values. Larger values of $PL$ indicate superior rotor performance since the rotor would require less power to generate the same amount of thrust. It can be seen that decreasing the value of $N_0$ not only increases the acoustic results, but it also significantly increases the value of $PL$ for a fixed thrust condition. This is due to the decreased power required to rotate fewer blades, which dominates over aerodynamic effects on the required power caused by increasing the distributions of $\theta_{tw}(r)$ and $\alpha(r)$. Similarly, less power is required for a lower value of $R$; however, unlike variations of $N_0$, decreasing the value of $R$ has a favorable effect on the tonal noise with slight adverse broadband noise effects. Table 3 shows that variations of $\Omega$ have the greatest effect on $PL$, with its reduction significantly increasing the rotor efficiency while decreasing the rotor noise. Since variations of both $\theta_0$ and $T_{design}$ had a direct impact on the distributions of $\theta_{tw}(r)$, $\phi(r)$, and $\alpha(r)$, decreasing these input features not only decreases both tonal and broadband noise, but also increases the value of $PL$, signifying increased rotor performance. Variations of $M$ have a very modest effect on the value of $PL$, causing a decrease in rotor performance with an increase in the value of $M$. Variations of $N$ and $XX$ also have a minimal effect on the value of $PL$ with a degradation in rotor performance for decreasing values of $N$ and $XX$. 

Table 3: Power loading at maximum and minimum input feature values.

<table>
<thead>
<tr>
<th>Input Feature</th>
<th>PL (lb/HP) Min.</th>
<th>PL (lb/HP) Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_0$</td>
<td>19.61</td>
<td>16.70</td>
</tr>
<tr>
<td>$R$</td>
<td>18.52</td>
<td>16.61</td>
</tr>
<tr>
<td>$\Omega$</td>
<td>20.09</td>
<td>15.23</td>
</tr>
<tr>
<td>$T_{design}$</td>
<td>17.98</td>
<td>17.11</td>
</tr>
<tr>
<td>$\theta_0$</td>
<td>18.00</td>
<td>17.08</td>
</tr>
<tr>
<td>$M$</td>
<td>17.73</td>
<td>17.36</td>
</tr>
<tr>
<td>$N$</td>
<td>17.42</td>
<td>17.69</td>
</tr>
<tr>
<td>$XX$</td>
<td>17.16</td>
<td>17.94</td>
</tr>
</tbody>
</table>
This research illustrates the use of machine-learning-based prediction modeling in characterizing the aerodynamics and aeroacoustics of rigid optimum hovering rotors over a broad range of design and operating conditions. A low-fidelity toolchain consisted of ANOPP’s PAS (Ref. 13) to calculate the aerodynamic thrust generated by the rotor, the total (i.e., induced and profile) power needed by the rotor, tonal (i.e., thickness and loading) noise at the fundamental blade passage frequency (BPF), and rotor inflow parameters, such as the distributions of $\phi(r)$ and $\alpha(r)$. The toolchain used the rotor inflow parameters to calculate broadband self-noise using ASNIFM (Ref. 14). Modern DoE was then employed to cre-

**CONCLUSIONS**

Figure 8: Collective pitch effect on tonal noise directivity, broadband noise directivity, twist distribution, inflow angle distribution, and angle of attack distribution. $N_b = 3$, $R = 7$ in, $T\text{design} = 2.25$ lb, $\Omega = 4750$ RPM, $M = 4.5\%$, $N = 35\%$, and $XX = 10.5\%$.

Figure 9: Camber effect on tonal noise directivity, broadband noise directivity, twist distribution, inflow angle distribution, and angle of attack distribution. $N_b = 3$, $R = 7$ in, $T\text{design} = 2.25$ lb, $\Omega = 4750$ RPM, $M = 4.5\%$, $N = 35\%$, and $XX = 10.5\%$, and $\theta_0 = 0^\circ$. 

Tonal loading noise.

Inflow angle distribution.

Broadband noise.

Angle of attack distribution.

Tonal thickness noise.

Twist distribution.

Tonal loading noise.

Inflow angle distribution.

Angle of attack distribution.
Artificial Neural Networks (ANNs) were trained over the data sets to model functional relationships between the input features. The low-fidelity tools were used to simulate the data points defined by the two design spaces to develop training and testing data sets for the machine learning prediction models.

ANNs were used to predict PL, tonal thickness and loading OASPL values, and broadband OASPL values along an arc of observers located 1.896 m away from the center of the rotor plane. Equation 1 and ANOPP’s PAS were also used to develop distributions of \( \theta_w(r) \), \( \phi(r) \), and \( \alpha(r) \) to establish physical aerodynamic insight. These predictions were conducted at maximum and minimum values of each respective input feature while maintaining all other features at their mean values, which allowed for a visual comparison of the effect of each input feature on the acoustic metrics. Values of PL at the maximum and minimum values of each input were also tabulated to gain further insight as to how rotor performance varied with changing input feature values.

It was shown that for an optimal hovering rotor, the tonal noise was dominated by loading noise and that the value of \( N_h \) had the greatest effect on the tonal noise. Decreasing the value of \( N_h \) decreased the value of \( \sigma \) for a fixed value of \( T_{\text{design}} \), which increased the distribution of \( \theta_w(r) \) and decreased the distribution of \( \alpha(r) \). These effects significantly increased the tonal loading noise while also increasing the value of PL, signifying an increase in rotor performance. Increasing the value of \( R \) had a similar effect on the acoustics as decreasing the value of \( N_h \) since this also decreased the value of \( \sigma \), but with a degradation in rotor performance. Increasing the value of \( \Omega \) increased both the tonal and broadband noise while decreasing the distributions of \( \theta_w(r) \), \( \alpha(r) \), and \( PL \), which was attributed to higher tip Mach numbers. Both variations in \( \theta_0 \) and \( T_{\text{design}} \) had similar effects on the distributions of \( \theta_w(r) \), \( \phi(r) \), and \( \alpha(r) \), causing an increase in tonal and broadband noise with a degradation in rotor performance. It was shown that the broadband noise was most sensitive to variations of \( \theta_0 \). The increase in both the distributions of \( \phi(r) \) and \( \alpha(r) \) was thought to increase broadband trailing edge separation noise, explaining the large sensitivity of broadband noise to variations of \( \theta_0 \).

Increasing the value of \( M \) was seen to reduce the distributions of \( \theta_w(r) \) and \( \alpha(r) \), which caused a minimal increase in tonal noise while slightly decreasing both broadband noise and the value of PL. Increasing the value of XX had a very similar effect as increasing the airfoil camber, so plots for this input feature were excluded from this work. The plots for \( N \) were also omitted since variations in \( N \) had negligible effects on all acoustic quantities and PL.

It can be concluded from this study that most of the input features modified the twist distribution of an optimum hovering rotor resulting in changes to both the rotor acoustics and performance. The tonal noise and PL were most sensitive to \( N_h \) and \( \Omega \) and the broadband noise was most sensitive to \( \theta_0 \) and \( T_{\text{design}} \). Since these ANNs can be used to predict aerodynamic/aeroacoustic quantities of interest in a matter of seconds, it is anticipated that they will be used for future design optimization studies for optimum hovering rotors.

Author contact: Christopher S. Thurman, Christopher.Thurman@nasa.gov

ACKNOWLEDGMENTS

This work was funded by the NASA Revolutionary Vertical Lift Technology (RVLT) project.

REFERENCES


