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ON THE PREDICTION OF PROPELLER TONAL NOISE WITH MACHINE LEARNING

Pedro Henrique de Carvalho
Rafael Gingena Cuenca
Filipe Dutra da Silva
Federal University of Santa Catarina, Joinville-SC, 89219-600, Brazil
pedrohcv23@gmail.com, rafael.cuenca@ufsc.br, filipe.dutra@teg.ufsc.br

Abstract. *From a historical perspective, propeller noise has been a community concern, mainly for areas with high air traffic such as airports and urban areas. Recently, the popularity of drones and other unmanned aerial vehicles (UAV) for in-city missions, such as package deliveries and surveillance, has motivated the investigation of propeller noise and the development of quieter devices and noise reduction systems. Aiming to investigate the noise impact of UAVs on community areas located on flight paths, a multilayer perceptron (MLP) neural network for regression was trained to model the propellers performance, using the Advanced Precision Composites (APC) database. The machine learning models were coupled with Hanson's load and thickness tonal noise prediction method to evaluate the noise for a ground observer. The repeated-kFold cross validation technique was implemented to evaluate the mean squared error (MSE) of 16 different MLPs configurations and the chosen one resulted in a MSE of the order 1 x 10^{-5}. Finally, the performance model was validated through comparisons with experimental data and, after that, the noise prediction model was coupled to it. Acoustics results showed good agreement with experimental data, highlighting the accuracy of the final model.*

Keywords: *Propeller noise, Aeroacoustics, machine learning, reduced order model, Propeller performance*

1. INTRODUCTION

In recent days, the use of drones and other unmanned aerial vehicles (UAVs) in populated areas has grown to such an extent that its use can be seen even in daily common tasks and recent expectations suggest that the use of these vehicles in urban areas tends to grow in the coming years. Ayamga *et al.* (2021) discuss that the increase in its use is related to its multitasking quality, being present in several areas of society, such as production, agricultural and military sectors.

Meanwhile, the noise generated by these vehicles has become a critical concern given that recent research indicates that traffic-related noise can cause problems associated with public health. According to Fritschi *et al.* (2011) the exposure to this excessive noise can strongly affect the population quality of life and in addition, it is estimated that in the coming years this exposure could aggravate cases of ischemic heart disease and sleep disorders. Aiming to contain this problem the International Civil Aviation Organization (ICAO) has gradually restricted the permissible noise levels that is generated by air vehicles.

According to Rizzi *et al.* (2020), the propulsive noise of the electric vertical take-off and landing (eVTOL) vehicles is a major concern for implementing this type of transportation. In order to estimate the sound pressure level (SPL) generated by propellers, in the last decades, several researchers have propose semi-analytical models to predict the SPL for different operation conditions. Gutin (1948) and Deming (1940) worked with the hypothesis that this noise should be composed of an harmonic component that could be divided into thickness and loading noise, the latter being dependent on the aerodynamic data of each propeller blade section and, in this way, they were able to develop noise prediction equations in the frequency domain. Hanson (1980) considered the thickness and loading distribution along the chord direction as an input in order to predict the tonal noise of a propeller.

Recently, the desire to develop propeller-driven objects has led to a high demand for establish methods capable of predicting the behavior of both the noise and the aerodynamic data generated by them. An example of this can be seen in the work of Herniczek *et al.* (2019) in which explores different semi-analytical noise prediction models coupled to the Blade Element Momentum theory (BEMT) to generate noise estimates that are then compared with experimental and computational fluid dynamics (CFD) simulations data. Another work that also explored the coupling of semi-analytical models for predicting tonal propeller noise with data obtained from CFD is presented by da Silva *et al.* (2022), where noise prediction was also obtained through the acoustic analogies proposed by Williams and Hawkings (1969).

In a different approach, some studies have developed semi-empirical methods that are obtained by coupling empirical data with a regression technique to model noise generation and propagation. In this sense, Heidmann (1979) uses various equations and graphs to define the noise spectrum based on the characteristics of a turbo-fan and then, Cuenca (2017) used this data in his work to train an artificial intelligence and finally generate the regression of a noise model to a scale model of a ducted fan. In this case, kriging regression was used (Krige, 1951).

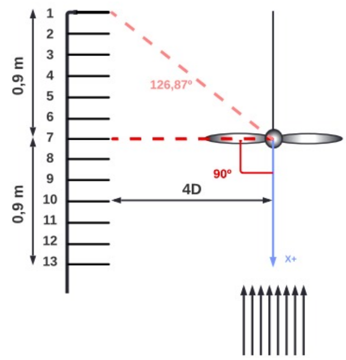
Following the idea of a model that is based in geometric parameters and operating conditions, this paper proposes the use of machine learning to obtain the aerodynamic input data for analytical noise predictions methods, aiming to create a model that meets robustness criteria and low computational cost. In this context, a neural network was implemented using the Advanced Precision Composites (APC) propeller performance database to replicate the thrust and power coefficient of a propeller, in this case using the multi-layer perceptron (MLP) regressor and the harmonic noise was predicted using the method proposed by Hanson (1980).

2. METHODOLOGY

2.1 Propeller geometry and experimental data

The noise prediction implementation was validated using the experimental data from Casalino *et al.* (2021). Figure 1a show the geometry of the two-blade propeller, such a propeller having a diameter (D) of 0.3 m and a NACA4412 airfoil profile. A total of 13 microphones were placed in a row at a distance of $4D$ from the axis rotation of the propeller as represented by Fig. 1b. All the measurements were performed at the fixed rotation of 5000 rpm, in 4 different operating conditions of freestream velocity of 0, 6, 10 and 15 m/s.

(a) Blade geometry of the propeller used by Casalino *et al.* (2021).



(b) Schematic representation of the experiment by Xavier (2022).

Figure 1. Information about the geometry and experimental tests from Casalino *et al.* (2021)

As the method from Hanson (1980) predicts the Tonal component, it was necessary to separate the tonal noise from the measured data. This task was done using Sree (2013) and Sree and Stephens (2016) technique that operated on the time domain pressure data and using the concept of blocks developed by Welch (1967). Before performing the separation, the signals were filtered by a high-pass filter to avoid the presence of spurious effects generated by frequencies below half the BPF. Thus, it was possible to separate the tonal and broadband components from the time series data. An example of the separation is illustrated in Fig. 2, where it shows a distribution of the power spectral density (PSD) for the microphone 9 at a freestream velocity of 6 m/s.

2.2 Propeller Harmonic Noise

The propeller harmonic noise can be divided in two components: loading noise and thickness noise. To predict the loading component, the analytical equation proposed in Hubbard (1991) was implemented, that requires a low computational cost compared to other related works (Deming, 1940) since it does not require analysis of the propeller by blade sections, but only its total load components (power and thrust) and geometry information at 80% of the blade span. The root mean square (rms) of the pressure at the m-th harmonic is calculated as,

$$P_{mL} = \frac{imBM_t \sin\theta}{\pi\sqrt{2}yD}\left(T\cos\theta - \frac{1}{z_{eff}^2 M_t^2 c_0}W\right)\Psi_L J_{mB}, \tag{1}$$

where P_{mL} is the loading root-mean-square (rms) sound pressure, i is the imaginary number, m is the harmonic of blade passing frequency, B is the number of blades, M_t is the mach number at the propeller tip, θ is the radiation angle from propeller axis to observer, y is the observer distance from propeller axis, T is the propeller total thrust, W is the propeller total power, Ψ_L is the Fourier transform of the chordwise loading, z_{eff} is the effective normalized radial coordinate (0.8 as proposed by Hubbard (1991)), c_0 is the speed of sound, J_{mB} is the Bessel function.

For the thickness noise component, the analytical method developed by Hanson (1980) was implemented based on the formulation proposed by Herniczek *et al.* (2019) for the rms pressure. The equation is dependent on the spanwise

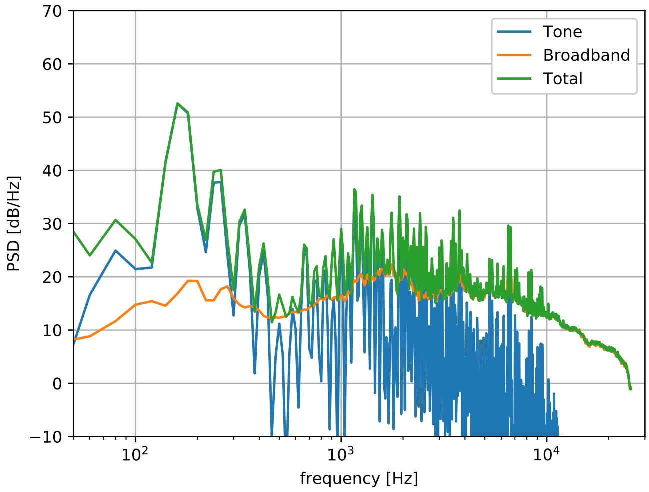


Figure 2. PSD of the propeller noise at microphone 9 at 6 m/s.

geometric characteristics of the blade as follows,

$$P_{mT} = \frac{-\rho_0 c_0^2 B \sin\theta}{4\sqrt{2}\pi(y/D)} \int_{hub}^{tip} M_t^2 (h/b) J_{mB} k_x^2 \Psi_V \, dr, \tag{2}$$

where P_{mT} is the thickness rms sound pressure at the m-th harmonic, ρ_0 is the air density, h is the maximum airfoil thickness, b is the airfoil chord, k_x is the wave number, Ψ_V is the Fourier transform of the chordwise thickness.

2.3 Perfomance Data and Model

To predict the noise load component, it is necessary to estimate propeller performance data such as thrust and power (Gutin, 1948). The propose of this investigation, is the use of the APC propeller data base, available at APC (2023). That data was normalized by:

$$Re = \frac{D^2 \pi n}{2\nu}, \tag{3}$$

where Re is the Reynolds number of the propeller, n the rotation frequency, and ν the air kinematic viscosity. The blade-tip Mach number is defined as,

$$M_t = \frac{D\pi n}{c_0}. \tag{4}$$

The design (J_d) and operational (J) advance ratios are defined as follows,

$$J_d = \frac{P}{D}, \tag{5}$$

where P is the propeller pitch,

$$J = \frac{V_0}{nD}, \tag{6}$$

The thrust coefficient (C_T) and the power coefficient (C_P) are defined as follows,

$$C_T = \frac{T}{\rho_0 n^2 D^4}, \tag{7}$$

$$C_P = \frac{W}{\rho_0 n^3 D^5}. \tag{8}$$

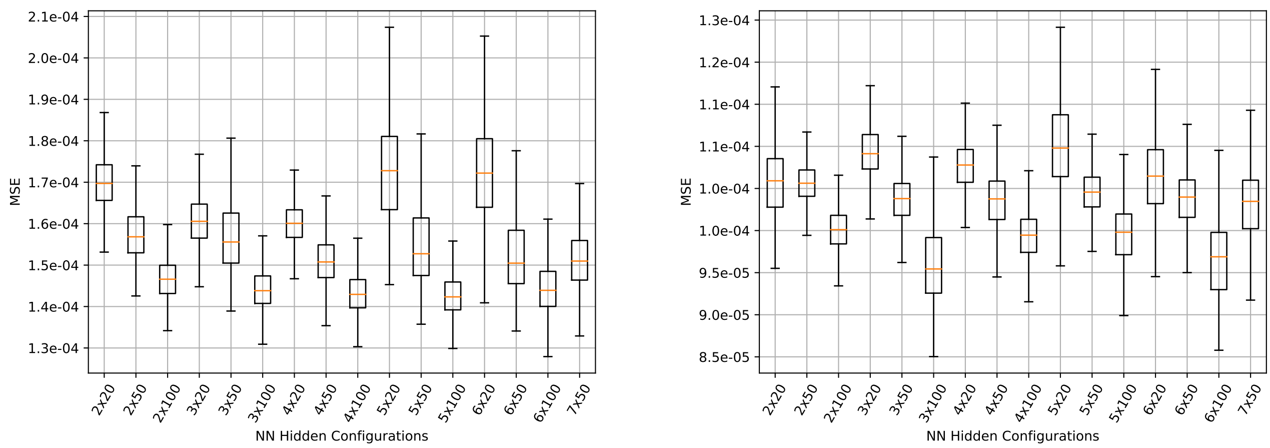
To perform the MLP regression (Galushkin, 2007), the implementation available on SciKit-Learn python library (Pedregosa *et al.*, 2011) was used. The limited-memory Broyden Fletcher Goldfarb Shanno (LBFGS) solver was choosen for the perceptron weight optimization, the strength of the L2 regularization term applied was 1×10^{-4}, the stopping criteria were 1×10^{-8} tolerance or 1×10^{4} epochs. Several MLP architectures were tested, varying the number of Layers from 1 to 5 layers, and 20, 50 and 100 perceptron per layers.

Aiming to evaluate the regression accuracy it is necessary to verify the occurrence of overfitting in the resultant MLP configuration and select the architecture which shows the greatest robustness. In other words, implement a cross validation method (Haykin, 1999). Here, the the repeated 10-fold cross validation method was chosen to evaluate the MLP's accuracy as described by Cuenca (2017). The adopted error metric is the mean squared error (MSE) (Chen *et al.*, 2023).

3. RESULTS AND DISCUSSION

3.1 Propeller Performance Model

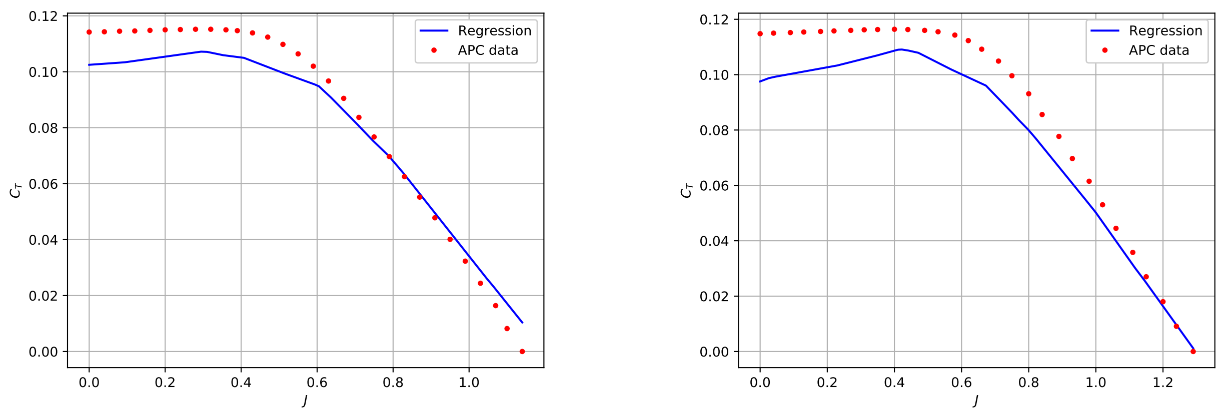
The results obtained in the cross validation for the MLP training (propeller power and thrust coefficients) for each of the MLP architectures are depicted in the boxplots in Fig. 3a and 3b. For both models, it is clear that increasing the number of neurons per layers reduces the MSE of the architectures. For the C_T model, the neural network (NN) containing 3 layers and 100 neurons per layer resulted in the lowest value of MSE, of the order 8.5×10^{-5} and for the C_P it is around 1.3×10^{-4} for the 6 layers with 100 neurons per layer.



(a) Power coefficient. (b) Thrust coefficient.

Figure 3. Boxplot of regressions for both coefficients.

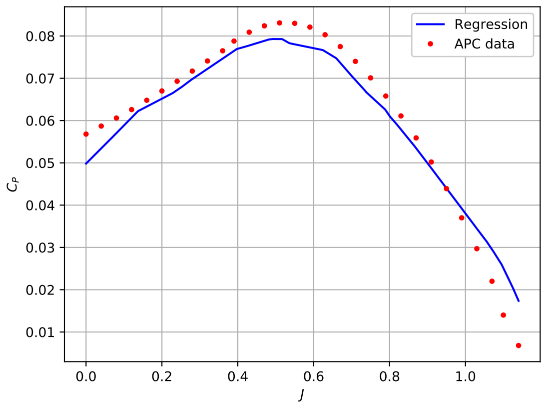
The resulting MLP model for the C_T coefficient can be seen as a function of the advance ratio compared with the original data from APC database, in Fig. 4a and 4b. It is evident that the model differs from the original data for the static thrust, however the agreement is good for the rest of the curve.



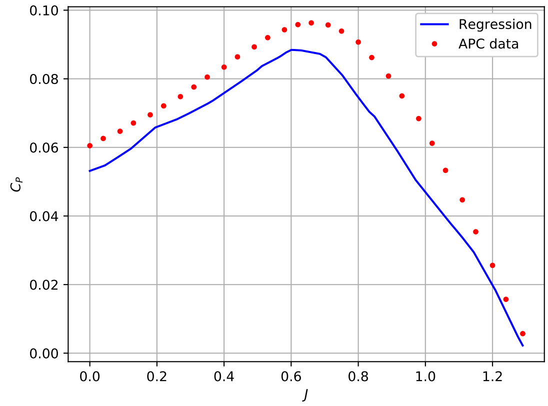
(a) 12x11 APC propeller. (b) 12x12 APC propeller.

Figure 4. Thrust coefficient regression

Furthermore, the same comparisons for the C_P coefficient are illustrated in Fig. 5a and 5b. By these comparisons, it is clear that the model again differs from the data on the static power but it actually shows good agreement for the rest of the curve, except for some intermediate advance ratios in the first case and for the second case the model seems to underestimate the C_P values by a small factor.



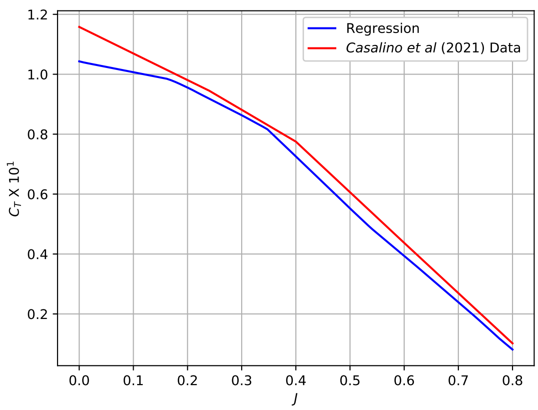
(a) 12x11 APC propeller.



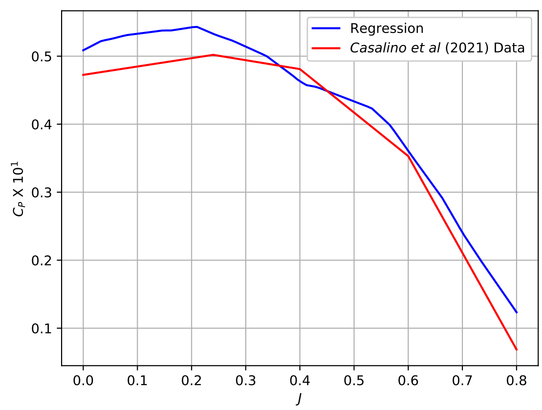
(b) 12x12 APC propeller.

Figure 5. Power coefficient regression

Finally, the prediction accuracy of the model for the propeller used by Casalino *et al.* (2021) was evaluated and the resulting prediction was compared with the experimental data. For the C_T coefficient comparison with experiments showed in Fig. 6a, it can be seen that the regression ended up following the same pattern as the previous comparisons of underestimating the thrust for the static case and again showed significant agreement with higher advance ratios, presenting an absolute mean error of 5.1×10^{-3}. While for the C_P coefficient, it can be seen that the regression ends up overestimating the values for low advance ratios but fits the experimental data along the curve, producing an absolute mean error of 2.9×10^{-3}.



(a) Thrust coefficient.

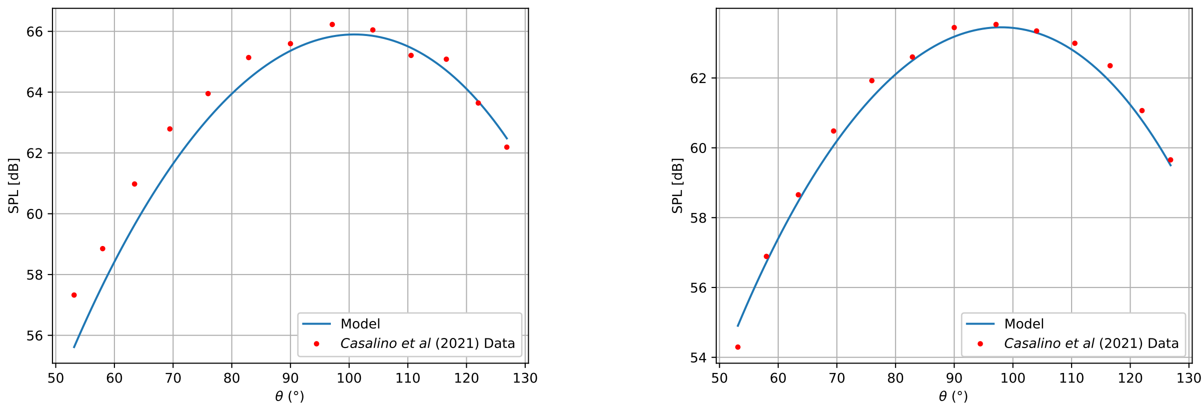


(b) Power coefficient.

Figure 6. Comparison between model estimate and experimental values

3.2 Validation of the Acoustic Predictions

In this section, to validate the implemented tonal noise prediction model, the experimental sound pressure level (SPL) were compared with the predicted value at two different advance ratio conditions (0.4 and 0.6) using the measured propeller performance data from Casalino *et al.* (2021) as input. Results of this comparison are shown in the Fig. 7a and 7b. The experimental data consists of only the tonal noise component at the first blade passing frequency (BPF). For the advance ratio of 0.4, the results show good agreement with the experimental data, predicting the position of the maximum SPL. Higher deviations are observed at low angles. The maximum deviation is 1.712 dB and the calculated mean absolute error was 0.681 dB. For the advance ratio of 0.6, the results show very good agreement with experiments. In this case, the maximum error is of 0.611 dB and the average error is 0.269 dB.

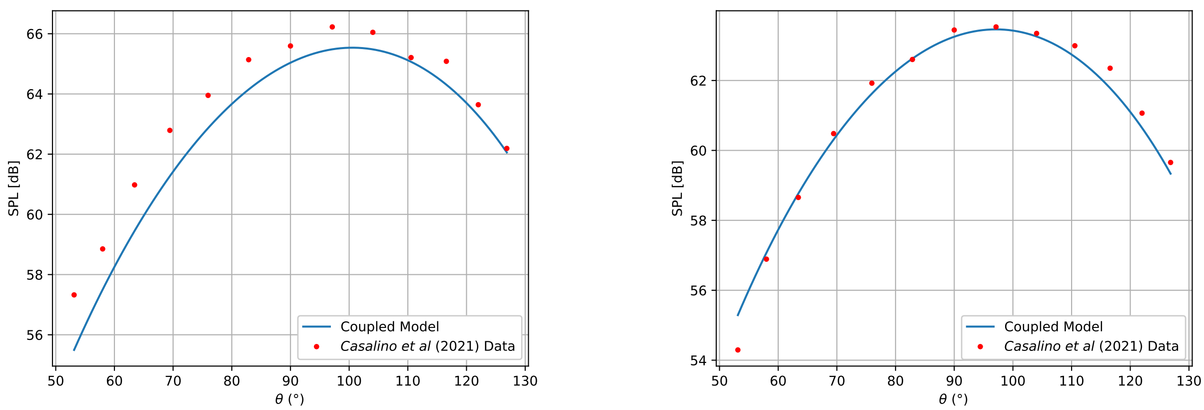


(a) Advance Ratio J = 0.4 . (b) Advance Ratio J = 0.6 .

Figure 7. Comparison between model estimate and experimental values

3.3 Machine learning coupled with the noise prediction model

Finally, with the MLP model for the propeller performance parameters evaluated and the acoustic prediction model already validated with the experimental data, it was possible to couple both models in order to obtain the final acoustic predictions. For this coupled model, the results were analyzed considering propeller advance ratios of 0.4 and 0.6, as shown in Fig 8a and 8b, respectively. For both cases, the model show a significant accuracy. For J = 0.4, the model ends up only slightly underestimating the SPL values in relation to the experimental data, presenting an absolute mean error of 0.891 dB and, even for the microphone that differs the most from the experimental data (located at 53.13°), the observed error was 1.828 dB. Furthermore, for J = 0.6, the model strongly fit the experimental data, presenting a mean error of 0.289 dB and a maximum error of only 0.996 dB.



(a) Advance Ratio J = 0.4. (b) Advance Ratio J = 0.6 .

Figure 8. Comparison between model estimate and experimental values

4. CONCLUSION

The results indicate a high robustness in the methodology used to model both the propeller performance values and the SPL generated by it for different observers. The resulting trained MLP prediction model for the aerodynamic data, i.e. the thrust and power coefficients, showed a good agreement with the tested cases and also with the experimental data. In addition, the harmonic noise prediction model also presented a low error initially using experimental aerodynamic data. When coupled, the final model once again showed good performance in relation to the experimental data, a fact that is a strong indicator of quality for this low computational cost noise prediction model. Finally, the model coupled with the neural network has the potential to be used to predict the acoustic noise generated by propellers of different geometries and under various operating conditions, and can thus be used to implement an algorithm focused on optimizing propeller geometry, guaranteeing stable performance.

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