Multiphysics

Efficient aeroacoustic modelling for drones with simulation and machine learning

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Introduction

In recent years, a significant proliferation in the development and commercialisation of small Unmanned Aircraft Systems (sUAS), commonly referred to as “drones”, has drastically changed the everyday use of civil airspace. Drones have captured the imagination of many entrepreneurs because they can offer a wide range of possibilities, i.e. commercial services, security, and environmental applications, in which classic manned aviation struggles.

The rapid progress in technological developments of drones has reduced their development, production, and operations costs. The democratisation of such technology offers various services to businesses and citizens while placing new demands on using the already congested civil airspace.

This rapid technological pace and the use of drones by civilians have left little time to develop appropriate regulatory frameworks concerning their safe and fair usage. Consequently, the absence of regulations may lead to misuse of this technology, negatively impacting its image, primarily due to noise emissions. Although they are not very loud, the frequency-shifting buzzing noise from drones is perceived as annoying by most people. Especially in take-off conditions, the propellers need to increment their rotation speed changing the overall acoustic signature in amplitude and tonal frequencies.

Challenge

Modern numerical techniques may help reduce noise from drones. The insights provided by the numerical simulation can guide engineers and scientists in discovering new strategies leading to quieter drone systems. A challenge for simulation in predicting drone noise is knowing the values of various flight parameters, such as the rotation speed of each rotor, crosswind, and pitch angle of the propeller blades. These parameters may vary in real-world situations, or their values are unknown. Different flight scenarios are described mainly by various propeller rotation speeds. In many cases, propeller speeds differ between the different propellers so that the drone can move forward, backwards, sideways, or rotate on its axis.

Such a situation renders the arduous task of addressing drone (or, in general, multi-propeller aircraft) noise using a deterministic approach, given the cost of the state-of-the-art computational techniques. This is especially true for low-cost drones in which the market revenue, the short product life cycle, and economic components do not justify such an investment.

Current computational techniques include high-fidelity computational fluid dynamics (CFD) techniques coupled with solutions of Ffowcs Williams-Hawkings' (FW-H) analogy and hybrid methods, including decoupled CFD and acoustics methods. Due to the high cost of CFD simulations, performing the required number of simulations to cover all possible situations is impossible.

Combined with clever computational aeroacoustic simulation techniques, Machine Learning (ML) could instantly provide game-changing predictions, covering all the different scenarios. With ML, we can predict the noise signature of a drone under conditions that are not evaluated by the computational aeroacoustic model.

A final challenge, especially for low-cost drones, is that they are equipped with brushless DC motors with no feedback control to determine the rotation speed. For this reason, the rotation speed is established by the supplied power and then measured using an optical tachometer. This creates a disconnect between measurements and simulation since simulation requires a fixed value. At the same time, analysis of the measured spectra showed a discrepancy between the measured rotation speed and the actual one.

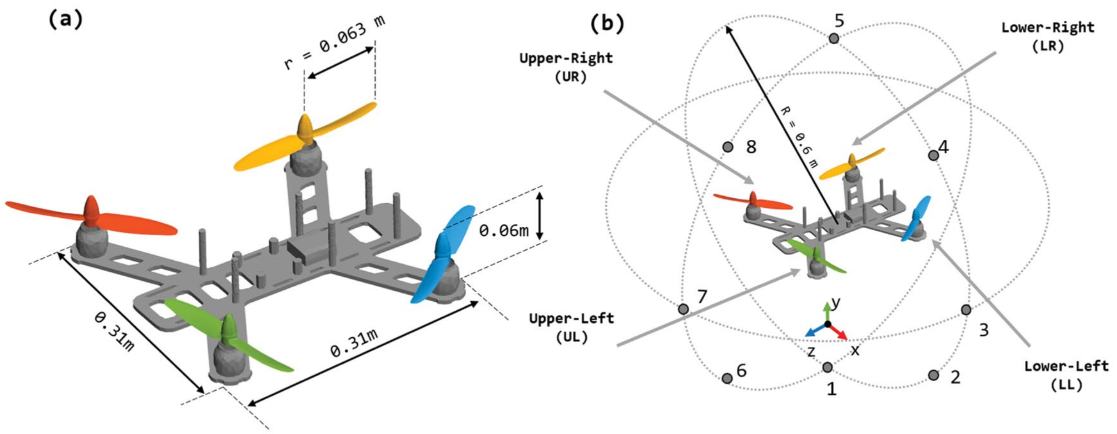

Figure 1: Drone configuration used in measurements and calculations: (a) Dimensions and directions of rotation; (b) Relative position of the microphones (not to scale).

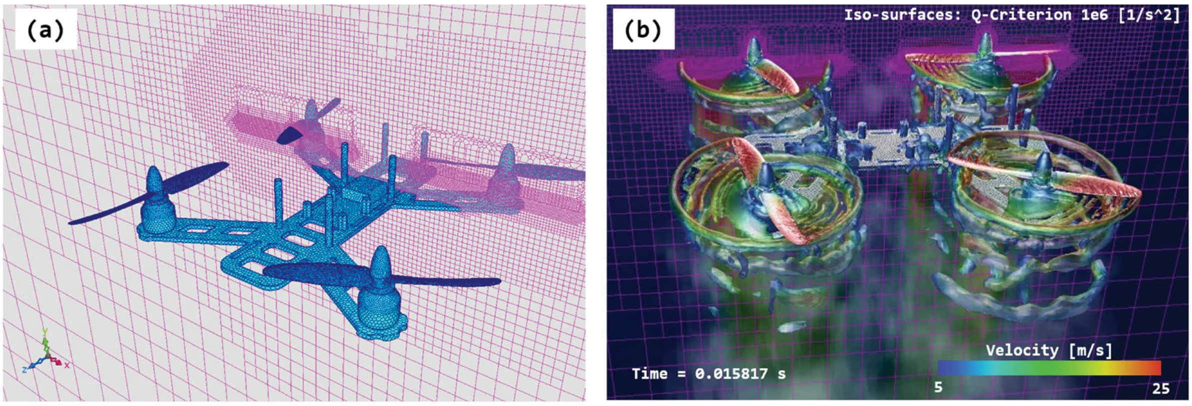

Figure 2: (a) Detail of the CFD mesh, (b) Instantaneous norm of the velocity and Q-criterion.

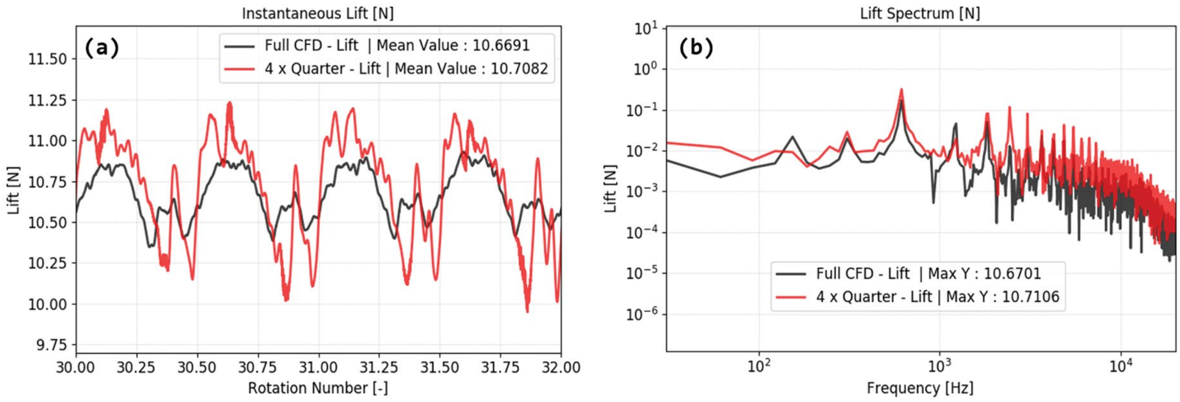

Figure 3: Instantaneous lift using the full CFD model (black line) and the quarter model (red line): (a) Time evolution between the 30th and 32nd rotation of the propellers; (b) Spectra for the instantaneous lifts.

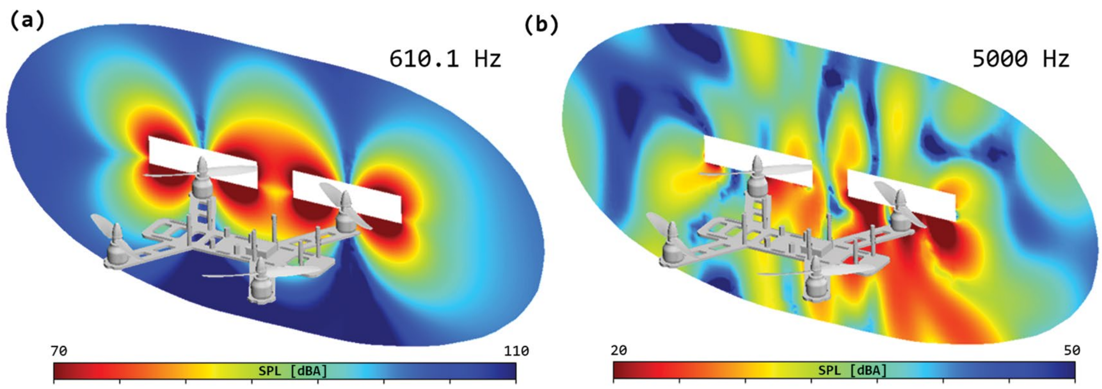

Figure 4: Pressure maps in dBA for 610.1 Hz (BPF) and 5,000 Hz. The four propellers rotate at 18,303 rpm.

Simulating the drone and optimising large simulations

The drone considered for this case is a small, low-cost quadcopter drone. Hosei University's Urban Air Mobility lab in Japan performed measurements of the drone's noise signature. Usually, low-cost drones are equipped with brushless DC motors with no feedback control to determine the rotation speed. For this reason, the rotation speed is established by the supplied power and then measured using an optical tachometer. Three different power supplies were considered, leading to the following measured speeds: 15,379 rpm, 17,140 rpm and 18,303 rpm.

The computational process is split into a Cradle CFD simulation using scFLOW and an aeroacoustic simulation using Actran.

For the Cradle CFD simulation, two configurations were built, one with the full 3D model with four propellers and a quarter model with one propeller and two symmetry conditions, which will be faster to solve and allows for easier post-processing later. Four rotating domains were placed in connection with the static domains for modelling the propellers by using sliding meshes.

An LES simulation is performed, costing about 7,550 CPU-hours for the full model and 3,160 CPU-hours for the more refined quarter model, respecting all stability and signal-processing criteria. The simulations were run for 87 rotations at the reference speed of 18,303 rpm, discarding the first eight rotations to only consider the statistically converged signal. The flow information (i.e. velocity, pressure, and density) was exported at each time step for use in the computation of aeroacoustic sources. The two configurations produce remarkably similar lift characteristics so that the quarter model can be used for the next step, the aeroacoustic simulation.

Upon completion of the Cradle CFD solution, Actran is used to calculate the aerodynamic sources and noise propagation. In the acoustic model for the complete drone, the aerodynamic sources from each propeller are placed onto their respective Lighthill surface. The model is valid up to a computational frequency of 5 kHz. The acoustic analysis of 492 frequencies solves in 185 CPU-hours. Since the time signal of the flow variables is sufficiently long, it is worth noticing that this is divided into sub-signals to generate seven sub-load cases per rotation speed deviation.

With this process established, the challenge now is to cover many possible scenarios regarding propeller rotation. Simulating them one by one would be costly. So, a more intelligent strategy is required, which will utilise the load case capabilities of Actran.

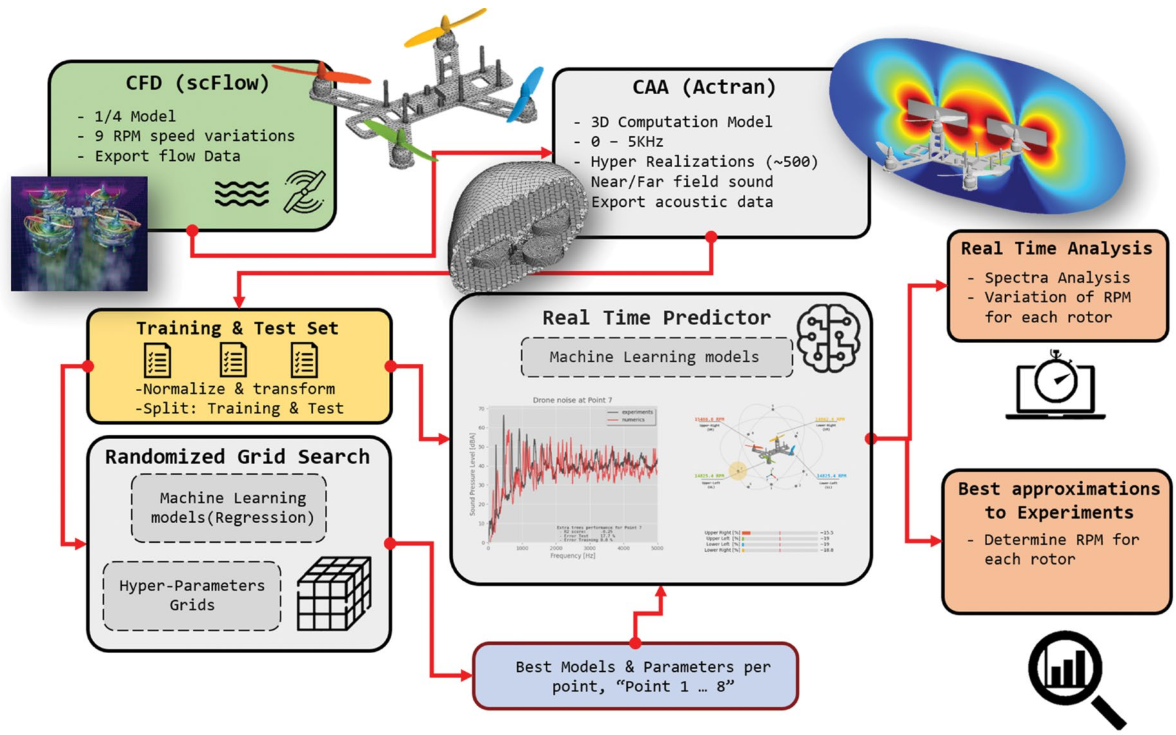

Figure 5: ML strategy in a combination of CAA and CFD simulation.

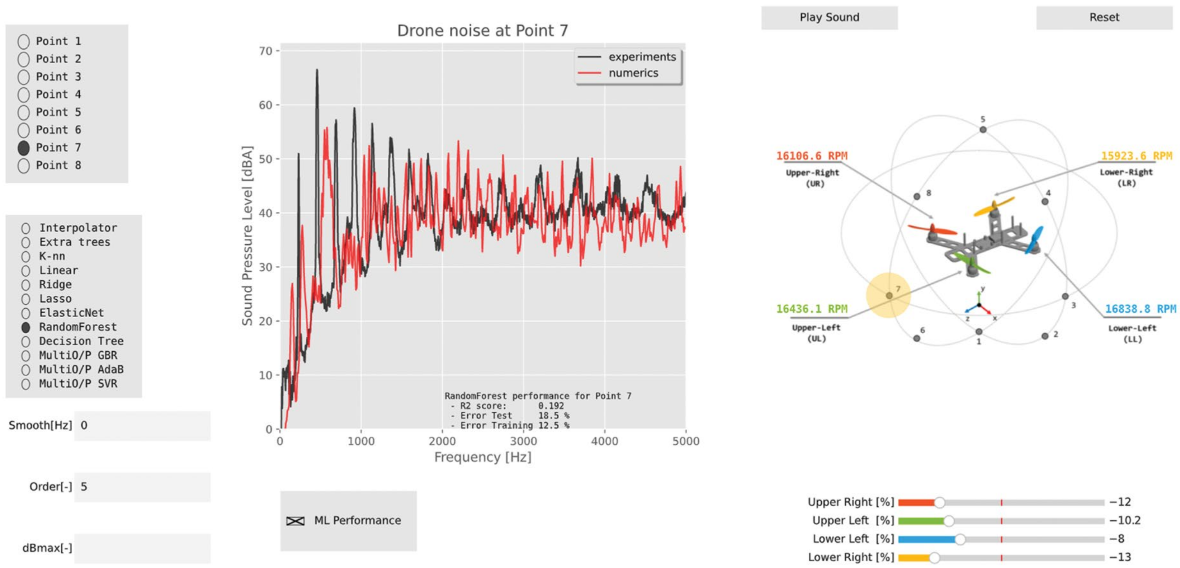

Figure 6: An application to generate noise results in real-time based on ML techniques.

Due to symmetry, Cradle CFD calculations are performed on a reduced quarter model by varying the rotation speed from -40% to 0% deviation from the selected reference rotation speed (18,303 rpm). The resultant flow information for each rotation speed (i.e. velocity, pressure and density) is exported for the computation of aeroacoustic sources. Then, the aeroacoustic sources are translated into the frequency domain and used in the Computational Aero Acoustics (CAA) solver to estimate the sound pressure level up to 5 kHz using 492 discrete frequency values. Given the nine rotation speed deviations computed for the four propellers and seven sub-load cases, the CAA solver's total load cases rose to 882 data samples.

Machine Learning to the rescue

Employing supervised ML techniques (decision trees and support vector machines) generates the noise spectrum based on the rotation speed inputs and trained on the combined simulation data. Because the data in the ML procedure originates from computational physics algorithms, the selection of ML features is already determined. They correspond to the deviations of rotation speed for each propeller. The modelling techniques were cross-validated, and hyper-parameter tuning identified the best approach with the minimum error at prediction. In the end, for the best model, a gradient-boosted tree, the maximum absolute error estimated is around 1.19 dBA, relatively low for acoustics comparison standards.

The models were imported into a graphical application enabling the engineers to get the noise spectrum in real-time depending on the rotation speed variation from the nominal (18,303 rpm). Engineers can view the spectrum for each microphone and play the measured sound for each microphone.

What comes next

This application is only an example or prototype of the potential of ML for drone noise and other applications. The future could include a fully functional, internet-connected web application where engineers could generate sound from the acoustic predictions and acoustic maps to visualise the noise propagation in real time.

In this case, the goal was to compare against measurements performed on a static rig. In the future, the model could be improved for real-world situations by adding other effects such as the pitch variation of the blades, complex propagation in model cities and neighbourhoods, wind speed and direction and many more effects.

The described methodology extends and applies to other multi-propeller aircraft configurations, such as passenger drones and fixed-wing aircraft with distributed propulsion.

By combining high-fidelity simulation data from world-class tools such as Cradle CFD and Actran with ML, drone design and certification for noise can become faster and more streamlined, and the new generation of drones can be safer and quieter.