Wing flutter control using artificial intelligence

ISAE-SUPAERO, Toulouse, France

funding : fully funded
start : October or November 2025
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Light aircraft with high aspect ratio wings typically suffer from wing flutter, an aeroelastic phenomenon that limits their flight speed. More specifically, above a critical flight speed, an aeroelastic instability arises that leads to the oscillation of the wing as a response to aerodynamic loads. In the worst case scenario, the wing can break under such structural stresses.

The aim of the PhD thesis is to assess whether an active control of the wing flap, through artificial intelligence, can help mitigate this phenomenon. The active control will rely on Reinforcement Learning (RL), an approach that seeks an optimal controller without prior modelization of the physics or knowledge of the physical mechanisms at play [1]. That is, the optimal controller is learned through a trial and error process where the RL algorithm constantly interacts with the environment (i.e. the system that we want to control, in this case the deformable wing in an airflow).

In the first part of the thesis, the candidate will apply RL to a fast aeroelastic model (figure 1) based on unsteady thin airfoil theory (Wagner's theory) and the equations of motion for pitch and plunge. On the contrary to most 2D aeroelastic models of wing flutter, the present model will be derived in the time domain to allow for real time control using RL. Here, the candidate will seek to understand the role of measurement noise and actuation frequency on the optimal control in view of the second part of the internship. The robustness of control with respect to physical properties (e.g. linear versus non-linear damping) will also be assessed.

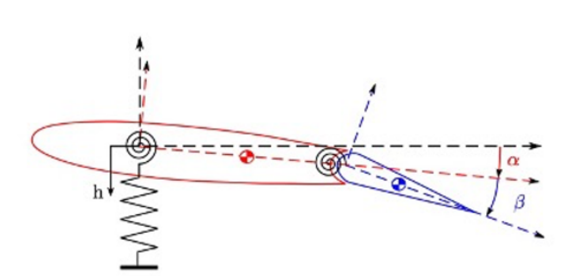

Figure 1: 2D model of wing flutter.

In the second part of the thesis, the previous analytical problem will be reproduced numerically. The aerodynamics will be computed by solving the Navier-Stokes equations either under their inviscid (Euler) or unsteady Reynolds-Averaged (URANS) form. In this framework, collecting samples to feed RL training is significantly more expensive than with the analytical model. This is a common issue when coupling RL with CFD (Computational Fluid Dynamics) and hence attention will be paid to sample efficiency [2].

In the last part of the thesis, the candidate will apply RL to a wind tunnel experiment. This challenging task requires to connect the RL framework (developped in the previous parts) to hardware devices in experiments. This raises many practical questions related to the role of measurement noise and acquisition/actuation frequency on the optimal control, for example. As opposed to the theoretical framework derived in the previous part, measurement noise and acquisition/actuation frequency are here imposed by 'real life' conditions (i.e. they are inherent to wind tunnel tests). In addition, other more fundamental questions will be addressed, related for example to transfer learning, i.e. in that case the ability to develop an optimal control based on both theoretical/numerical models and experiments.

The PhD thesis will be conducted at the Department of Aerodynamics, Energetics and Propulsion (DAEP), in collaboration with the Department of Mechanics, Structures and Materials (DMSM), at ISAE-SUPAERO in Toulouse. It is fully funded and part of a larger project involving internships and post-docs.

DAEP and DMSM are looking for a candidate (Master level) with a strong background in one or more of the following topics : aerodynamics, structural dynamics and control. Knowledge in Artificial Intelligence and Reinforcement Learning is a plus. Applications should be sent to michael.bauerheim@isae.fr and thierry.jardin@isae.fr (CV, recommendation letter, transcripts and previous internship reports if relevant).

References

[1] Martin, B., Jardin, T., Rachelson, E., & Bauerheim, M. (2024). Vortex gust mitigation from onboard measurements using deep reinforcement learning. *Data-Centric Engineering*, 5, e47.

[2] Berger, S., Ramo, A. A., Guillet, V., Lahire, T., Martin, B., Jardin, T., Rachelson, E, & Bauerheim, M. (2024). Reliability assessment of off-policy deep reinforcement learning: A benchmark for aerodynamics. *Data-Centric Engineering*, 5, e2.