A tailored Machine Learning Surrogate to improve Rotorcraft Trajectory Design

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Mots-clés : *black-box optimization, surrogates, artificial neural networks*

1 Introduction

Rotary-wings aircraft (also called rotorcraft) are essential in the aeronautical domain, thanks to their abilities to conduct specific missions that other types of aircraft cannot perform. However, numerous complaints rise to the operators regarding noise annoyance. Considering the foreseen growth in rotorcraft operations above cities with the emergence of Urban Air Mobility (UAM), the noise reduction of rotorcraft operations has become necessary. In this study, we consider a specific type of rotorcraft (helicopters) and aim at designing optimal trajectories in such a way that the associated noise footprint is minimized.

We define a trajectory as a succession of waypoints, which are interpolated afterwards to get a smooth flyable trajectory. Each waypoint is described by four variables : x, y and z represent the 3D position of the waypoint, while v sets the speed of the rotorcraft at the waypoint. The decision variables of the problem are (x_i, y_i, z_i, v_i) for all $i \in \mathcal{W}$, where $\mathcal{W}$ is the set of waypoints. The number of waypoints $N_{\mathcal{W}} = |\mathcal{W}|$ is a data of the problem, depending on the problem instance.

In this study, the objective function does not have an analytical expression in terms of the decision variables, but it is evaluated through a numerical simulation performed by a black-box industrial software. Therefore, we do not have access to its gradient either. We thus focus on black-box optimization methods that do not rely on the use of derivatives.

2 A machine learning-based surrogate

In this study, we use the MADS (Mesh-Adaptive Direct Search) algorithm [1] through its NOMAD [4] implementation, as a state-of-the-art Black-Box Optimization (BBO) method, with a guarantee of local convergence.

The evaluation of a candidate solution (i.e. a trajectory) is performed through a black-box simulation which, as for many industrial problems, is based on a complex physical model. These simulations provide accurate values for the objective, but are particularly computationally expensive. In order to reduce the number of calls to such simulator, we may resort to surrogate models. Most of the time, surrogates are built according to generic methods (polynomial approximation, radial basis function, Gaussian process regression…) such as in [3, 5]. In this study, we rely on our knowledge of the problem to propose an application of a widely used machine learning technique to build a surrogate.

The goal is to learn how the physical model behind the black-box works, i.e. the relationship between a given rotorcraft configuration and the associated noise at a given position on the ground. Multi-layers perceptrons (MLPs) [2] are known to be efficient to estimate complex non-linear relations. Additionally, they are typically adapted to the shape of the considered data : a vector of n inputs features and a single output. The input features gather noise-dependent rotorcraft flight conditions (speed and rate of descent), the direction and distance between the rotorcraft position and the target ground position. The single output is the value of noise at the target ground position. A set of input features examples has been generated according to probabilistic distributions, which have been defined from statistics of rotorcraft flights. The associated noise values have been evaluated off-line by the black-box simulator. The resulting couples input features/noise $(\mathbf{x}_k, L_k) \in \mathbb{R}^{n+1}$ are called examples. The network has been trained minimizing the following loss function : $\sum_k (L_k - \tilde{L_k})^2$, where $\tilde{L_k}$ is the value of noise estimated by the MLP for the input $\mathbf{x}_k$ of the example $(\mathbf{x}_k, L_k)$.

Numerical results using the proposed surrogate within the MADS algorithm are promising in terms of both computational time savings and accuracy of the computed solution.

3 Conclusion

In this study, we propose a surrogate based on machine learning that is tailored to our problem. Such surrogate is used within the MADS algorithm to improve its computational performance in the scope of rotorcraft trajectory optimization in order to minimize its noise footprint. The benefits of using the proposed surrogate are shown trough numerical experiments.

Références

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