

A PRACTICAL OPTIMIZATION FRAMEWORK FOR HIGH-DIMENSIONAL AERODYNAMIC DESIGN USING SINGLE- AND MULTI-FIDELITY BAYESIAN METHODS

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Abstract

This work presents a comprehensive computational framework for the aerodynamic design optimization of complex fan casing using both single- and multi-fidelity Bayesian optimization. In many industrial applications, evaluating aerodynamic and aero-acoustic performance relies on computationally demanding Computational Fluid Dynamics (CFD) simulations performed on high-performance computing clusters. For such systems, direct optimization via high-fidelity evaluations is prohibitively expensive, necessitating the use of advanced surrogate-modeling techniques to enable efficient design space exploration.

To overcome the inherent “curse of dimensionality” associated with complex CAD geometries we first formalize a constraint-driven parameterization strategy. By imposing functional dependencies between geometric variables and applying sets of constraints, the framework effectively reduces the dimensionality of the design space while ensuring that all generated models maintain strict geometric and manufacturing feasibility.

Operating within this parameterized space, the developed framework allows for the systematic benchmarking of single-fidelity Bayesian optimization against two distinct multi-fidelity strategies. The first is a screening-based approach, which executes the Bayesian optimization loop entirely on computationally cheaper low-fidelity models (e.g., coarse mesh simulations) and subsequently validates only the most promising candidate designs using the high-fidelity model. The second is a joint multi-fidelity approach, which utilizes a linear autoregressive surrogate model trained simultaneously on a mixed dataset of coarse and fine simulations, explicitly modeling the high-fidelity response as a scaled low-fidelity response plus a correction term.

Furthermore, a significant challenge in automated, simulation-driven optimization is the occurrence of numerical failures during CAD updates, meshing, or solving. To ensure algorithmic stability, the framework incorporates a robust fallback mechanism that handles failed evaluations during adaptive sampling by systematically assigning penalized surrogate values or replacing failed acquisition

points with randomized feasible alternatives, thereby preventing the optimizer from stalling.

We evaluate the performance of these strategies in terms of aerodynamic performance gains against the total computational budget required. The empirical results demonstrate that both multi-fidelity strategies successfully match or exceed the optimization quality of standard single-fidelity (high-fidelity only) approaches while requiring substantially less computational time. Ultimately, this work provides a structured, highly robust methodology for deploying multi-fidelity Bayesian algorithms to accelerate design iteration cycles in computationally expensive fluid dynamics problems.