Doctoral Dissertation
Doctoral Program in Aerospace Engineering (36^{th}cycle)

Advanced Optimization Methods for Design and Diagnostic Problems in Aerospace

By

Francesco Di Fiore
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Supervisor(s):
Prof. Dr. Ing. Laura Mainini, Supervisor
Prof. Paolo Maggiore, Supervisor
Dr. Ing. Matteo D.L. Dalla Vedova, Co-Supervisor

Doctoral Examination Committee:
Prof. Ali Elham, University of Southampton
Prof. Vassili Toropov, Queen Mary University of London
Dr. Nathalie Bartoli, ONERA
Dr. Ana Paula Cuco, EMBRAER
Dr. Vladmir Balabanov, University of Colorado

Politecnico di Torino
2024

Abstract

In science and engineering, the development of complex systems involves many-query optimization problems to identify both optimal design configurations to satisfy competing requirements, and states of the system to monitor their health status. The adoption of high-fidelity models for those optimization problems would be beneficial to identify superior optimization solutions, but would prohibitively rise the demand for computational resources and time required for every query. Multifidelity Bayesian Optimization (MFBO) combines information from models at different levels of fidelity to accelerate the optimization procedure: fast low-fidelity models are massively queried to explore different combinations of optimization variables while high-fidelity models are wisely evaluated to sparingly refine the accuracy of the optimization solution. Most existing MFBO algorithms adopt a suboptimal greedy approach which measures the utility of evaluating the objective function only at the immediate next iteration, and are sequential in nature precluding the parallel computation of high-fidelity models. Another limitation of MFBO lies in the purely data-driven search of optimal solutions which does not include explicit information about the physical domain of the system of interest.

In the first part of this thesis, we propose a Non-Myopic Multifidelity Bayesian Optimization framework (NM2-BO) to grasp the long-term reward from future steps of the optimization. Our computational strategy comes with a two-step lookahead policy that maximizes the cumulative reward obtained measuring the improvement in the solution over two steps ahead. We demonstrate NM2-BO for a large set of analytical benchmark problems and an aerodynamic design optimization problem. Moreover, we devise a Non-Myopic Multipoint Multifidelity Bayesian Optimization (NM3-BO) which relies on a two-step lookahead policy and a local penalization strategy to measure the future utility achieved evaluating multiple design configurations simultaneously. We demonstrate NM3-BO for the multidisciplinary design optimization of a space vehicle.

In the second part, we propose a generalized formulation for physics-aware MFBO (PA-MFBO) to embed forms of domain awareness during the optimization procedure. We formalize a bias in the search that captures the physical structure of the domain. This permits to partially alleviate the data-driven search from learning the domain properties on-the-fly, and sensitively enhances the management of multiple sources of information. PA-MFBO is demonstrated for an aerodynamic design optimization and a structural health monitoring problem. In addition, we develop a non-myopic formulation of the PA-MFBO algorithm (PA-NM2BO) which combines a lookahead policy with the physics-aware search characterizing the PA-MFBO algorithm. PA-NM2BO is validated against wind-tunnel data for an aerodynamic design optimization problem.

In the third part of this thesis, we propose a computational framework to accelerate diagnostics optimization problems to identify onboard incipient damages affecting complex systems. This procedure typically requires an expensive large amount of high-dimensional signals acquired through numerical models of the system. We devise the FREEDOM – Fast REliability Estimate and incipient fault Detection Of Multiphysics aerospace systems – algorithm to address such limitations in diagnostics. FREEDOM combines an original two-stage compression to compute an optimally reduced representation of the diagnostics signals for the minimum demand of onboard resources, and a single-fidelity Bayesian optimization scheme to infer multiple fault modes affecting the equipment. In addition, we extend the FREEDOM methodology to incorporate high-fidelity models directly in the diagnostics procedure, and devise the multifidelity FREEDOM algorithm (MF-FREEDOM). MF-FREEDOM relies on a multifidelity Bayesian scheme to identify fault parameters from the compressed signals: variable cost and fidelity models are optimally queried for a major reduction of the overall computational expense. The FREEDOM and MF-FREEDOM frameworks are demonstrated and validated for aerospace electromechanical actuators for flight controls affected by incipient multimodal faults.