Paper ID: 89402
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IAF SPACE SYSTEMS SYMPOSIUM (D1)
Systems Engineering Approaches, Processes and Methods (6)

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MULTIFIDELITY ACTIVE LEARNING FOR THE DESIGN OF SPACE VEHICLES

Abstract

The multidisciplinary design optimization (MDO) of space vehicles presents many challenges associated with the variety of physical domains involved and their coupling. Examples are capsules for the transfer of astronauts to the international space station and for future Lunar and Martian exploration missions. For these vehicles, aerodynamics and thermodynamics phenomena are strongly coupled and relate to structural dynamics and vibrations, chemical non equilibrium phenomena that characterize the atmosphere, specific re-entry trajectory, and geometrical shape of the vehicle body. The design and optimization of those capsules would largely benefit from accurate simulations of those physical phenomena through high fidelity large scale multidisciplinary analysis. However, those high fidelity simulations usually require significant computational effort unfeasible during the preliminary design phase and trade off analysis.
Multifidelity methods are a class of machine learning techniques that permits to efficiently accelerate the exploration and evaluation of design configurations through the principled combination of disciplinary analysis at different levels of fidelity, accuracy and computational cost. This presentation focuses on multifidelity Bayesian optimization (MFBO) as an active learning procedure where the learner adaptively combines less expensive disciplinary analysis with a sparingly selection of costly high fidelity simulations to efficiently address the given design optimization goals. Within MFBO, the integration and interactions between levels of fidelity over multiple disciplines represent a key challenge for the MDO of space systems: standard methodologies limit the combination of multiple levels of fidelity to a single disciplinary analysis, without including potentially available levels of fidelity for the remaining disciplines.
To address this limitation, we present an original MFBO framework that leverages different fidelity spectra for multiple disciplinary domains. In particular, our strategy comes with an original active learning scheme to adaptively select the best combination of levels of fidelity over multiple domains to maximize the reward with respect to specific design optimization goals. This allows to tailor the selection of each physical model to increase the efficiency of the learning procedure using at best a limited amount of high fidelity data and resource budget to sensitively improve the design solution. Our method is demonstrated for the MDO of the Orion capsule considering the availability of multiple levels of fidelity for the simulation of the aerothermodynamic and thermo-structural domains.