Multifidelity Learning for the Design of Re-Entry Capsules

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The design and optimization of re-entry capsules presents many challenges associated with the variety of physical domains involved and their couplings. 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 body. The design and optimization of these capsules would largely benefit from accurate analyses of the re-entry flow field through high-fidelity representations of the aerothermodynamic phenomena. However, those high-fidelity representations are usually in the form of computer models for the numerical solutions of PDEs (e.g. Navier-Stokes equations, heat equations, etc.) which require significant computational effort and are commonly excluded from preliminary multidisciplinary design and trade-off analysis.

This presentation discusses the use of multifidelity methods to integrate high-fidelity simulations in order to obtain efficient aerothermodynamic models of the re-entering vehicles. Multifidelity approaches allow to accelerate the exploration and evaluation of design alternatives through the use of different representations of a physical system/process, each characterized by a different level of fidelity and associated computational expense. By efficiently combining less-expensive information from low-fidelity models with a principled selection of few expensive simulations, multifidelity methods allow to incorporate high-fidelity costly information for design analysis and optimization. Specifically, we propose a multifidelity active learning strategy to accelerate the multidisciplinary design optimization (MDO) of a re-entry vehicle. The active learning scheme is formulated to be both data-driven and domain-aware, and is implemented for the design of an Orion-like re-entry capsule. The MDO problem comprises trajectory analysis, propulsion system model, aerothermodynamic models, and structural model of the thermal protection systems (TPS). The design objectives are the minimization of the propellant mass burned during the entry maneuver, the structural mass of the TPS and the temperature reached by the TPS structure. The results show that our multifidelity scheme allows to efficiently improve the design solution through a limited number of high-fidelity evaluations.