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MULTIFIDELITY OPTIMIZATION TRACK NUMBER 700 (NUMERICAL METHODS AND ALGORITHMS IN SCIENCE AND ENGINEERING)

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ABSTRACT

In order to reduce computational time required by some model evaluations, multifidelity techniques are increasingly used in a large community [1]. Predictions and design engineering decisions can be made using a variety of information sources that range from experimental data to computer models. These information sources could consist of different mathematical formulations, different grid resolutions, different physics, or different modeling assumptions that simplify the problem. This leads to information sources with varying degrees of fidelity, each with an associated accuracy and querying cost. For optimization purpose, a hierarchy in the different available models can be imposed [2, 3] or not [4, 5] leading to different techniques aiming at reducing computational costs. Some approaches are based on gradient knowledge, data fusion, surrogate models, trust region management, adaptive sampling, Bayesian optimization, ...The objective of the symposium is to present different methods and some associated toolboxes. Some examples in aeronautical or space applications will be given to illustrate the efficiency of the proposed techniques.

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