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SURROGATE MODELS BASED ON HIGH FIDELITY NUMERICAL SIMULATIONS FOR ROCKET ENGINES INJECTOR DESIGN

Abstract

Liquid rocket engines (LRE) represent one of the most critical systems of a launcher as well as the most expensive. With the advent of the New Space industrial actors, there is the clear need to decrease the price of access to space. In this context, it is fundamental to develop innovative methodologies enabling to decrease the cost of engine development while keeping a high-fidelity level of the critical component's description. In the present paper, we develop an approach to jointly use computational fluid dynamics of reactive flows and deep learning for the generation of surrogate models of injectors and combustion chambers. These models are meant to efficiently help the engineer in the preliminary design phase. Indeed, LRE preliminary design is usually done by making use of system tools based on semi-empirical correlations. The associated error strongly depends on the fidelity of the component's models. In particular, low order models work poorly for injector elements and combustion chambers that are characterized by the highly non-linear phenomena associated with high pressure turbulent diffusion flames. Large Eddy Simulations (LES) have demonstrated the capability to be accurate and predictive for the description of turbulent diffusion flames in rocket engine chambers in representative conditions. Moreover, they allow to retrieve the description of the flame dynamics. The drawback is the high computational cost which does not allow to use LES in the framework of an optimisation process. We propose to use different deep learning algorithms on a LES database in order to extract surrogate models able to reproduce the LES with a very low inference time (in the millisecond range). The reference case is a single coaxial injector, burning gaseous methane and oxygen at 20 bar. The design of experiments (DOE) is built by varying the injector geometry (recess and chamber diameter) and the O/F ratio. Fully connected neural networks will be used for low dimensional quantities (averaged quantities, profiles) and convolutional neural networks for the field quantities. The approach has been yet developed on RANS data in recent publications by the authors. One of the major difficulties when going from RANS to LES is the generation of a proper DOE allowing to obtain acceptable surrogate models while keeping a low number of design points. Different strategies will be investigated to face this issue, including the use of the yet developed surrogate models on the RANS database. Finally, the obtained models will be compared and analysed.