Uncertainty propagation in multiphysics systems of solvers: application to robust space object reentry predictions

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Since the beginning of space exploration, the number of orbiting space objects is dramatically increasing and critical Earth orbits, such as the Geostationary Orbit (GEO), are saturated with non functioning satellites. The "Loi relative aux Oprations Spatiales" (LOS, Law of Space Operation) legally obliges space companies like ArianeGroup to deorbit end-of-life objects and to ensure that the reentry in the Earth atmosphere of these objects presents no risk for human assets.

To assess the risk associated with a reentry event, ArianeGroup (AG) needs to numerically quantify the human risk caused by one of their space objects. The numerical tool in use at AG to simulate the reentry of space object is a system of solvers (SoS) consisting of a set of interdependent solvers coupled together. It includes a trajectory solver coupled with an aerodynamic solver, a probabilistic fragmentation model and an ablation solver. These physical models involve many unknown parameters and dedicated uncertainty quantification methods are needed to assess the reliability of the simulation-based predictions. Propagating uncertainties in a system of solvers can be challenging, due to the coupling effects on the dependences of the trajectory with respect to the uncertain input and the computational cost arising from the sequential evaluation of multiple solvers. In these situations, standard uncertainty propagation methods are too costly and alternative methods dedicated to SoS have to be derived. In this work, we propose an original method for constructing a system of Gaussian Processes (SoGP) to form a surrogate model of a system of solvers. The SoGP is composed of a set of Gaussian Processes (GP) that reproduce the structure of the SoS under study. Each solver of the SoS is associated with a GP in the SoGP which is trained to approximate its corresponding solver. The prediction of the SoGP is not Gaussian as it is generally the composition of GP models.

The advantages of the SoGP, compared to constructing a single GP for the whole system at once, are essentially the following. First, the SoGP has a richer structure and offer more flexibility, and therefore it can fit a larger range of functions. Second, training the SoGP requires learning multiple but usually simpler individual solvers, possibly adapting the training efforts. On

the contrary, a global GP model needs to learn the (generally) more complex mapping between the SoS inputs and its outputs and requires the simulation of the whole system. Finally, SoGPs have the ability to propose a predictive error estimate that can be used in active learning strategies. In this work we propose an original active learning strategy to efficiently increase the accuracy of SoGPs. We are able to identify new training samples for each GP and select a subset of GPs to be trained. To do so, we derive a predictive variance decomposition of the SoGP into contributions from individual GP. The SoGP framework is validated on analytical functions and applied to construct a surrogate of the space objects reentry system of solvers used at ArianeGroup and predict the ground impact point. Using SoGP brings major improvements, in terms of precision, compared to using single GP model.