

## SCRAMJET Design Optimization using SNOWPAC in Dakota

SNOWPAC (Stochastic Nonlinear Optimization With Path-Augmented Constraints) [Augustin & Marzouk 17] is a method for stochastic derivative-free optimization, developed to treat nonlinear constrained optimization problems with uncertain parameters. These uncertain parameters represent, for example, a lack of knowledge about the system under consideration, or other errors in the models entering the objective and constraints. Optimization in these settings employs measures of robustness and risk in order to describe a suitable solution—for instance, to identify solutions that are relatively insensitive to parameter uncertainties.

SNOWPAC extends the path-augmented constraint framework introduced by NOWPAC [Augustin & Marzouk 14], via a noise-adapted trust region approach and Gaussian process approximations. It solves optimization problems where Monte Carlo sampling is used to estimate robustness or risk measures comprising the objective function and/or constraints. We consider problems where expensive black box model evaluations are needed to construct these estimates, and thus we focus on a small sample size regime. This regime involves significant noise in the estimators, which slows the optimization process. To mitigate the impact of noise, SNOWPAC employs Gaussian process regression to smooth models of the objective and constraints in the trust region. In a recent development, SNOWPAC has been integrated with the Dakota framework, which offers a highly flexible interface to couple the optimizer with different sampling strategies and surrogate models.

In this presentation, we showcase the combined SNOWPAC-Dakota capability by performing design optimization under uncertainty in two challenging problems: a bump in a 2D supersonic duct and supersonic turbulent spray combustion in a SCRAMJET engine. The SCRAMJET follows the HIFiRE design and is modeled by an LES simulation code developed by Sandia National Laboratories. We compare deterministic optimization results with results obtained by introducing uncertainty in the inflow parameters. As a sampling strategy, we contrast simple Monte Carlo sampling with more sophisticated multilevel Monte Carlo approaches. Here, Dakota serves as the driver of the optimization process, employing SNOWPAC as optimization method on the black box problem. We show that all approaches provide reasonable optimization over the design while seeking/maintaining feasibility in the final minimized objective. Furthermore, we see significant improvements in the computational cost when employing multilevel approaches that combine solutions from different grid resolutions.