FORMULATIONS FOR SURROGATE-BASED OPTIMIZATION UNDER UNCERTAINTY

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Many optimization problems must be performed in the presence of inherent variability (aleatory/irreducible uncertainty) or uncertainty resulting from a lack of knowledge (epistemic/reducible uncertainty). Without due attention to these uncertainties, designs will be driven to the limits of the deterministic constraints, leaving little latitude for variability and resulting in unreliable designs. The primary challenge in introducing uncertainties into these optimization procedures is to develop rigorous techniques with supporting convergence theory that avoid excessive computational expense.

In this presentation, various approaches to optimization under uncertainty are surveyed and formulations for optimization under uncertainty employing surrogate models are investigated in detail. A surrogate model may appear at the optimization level, at the uncertainty quantification level, or both, and may involve either data fit or model hierarchy surrogates. Of critical interest is the extension of provably-convergent surrogate-based techniques for deterministic optimization to these surrogate-based optimization under uncertainty formulations. Key components include use of a trust-region globalization and satisfaction of the consistency and verification requirements from the deterministic provable-convergence theory.

The DAKOTA software framework is used to provide the foundation for prototyping and benchmarking of these formulations. Two analytic test problems and one engineering problem are solved using the different methods. Results indicate that surrogate-based optimization under uncertainty formulations show promise in reducing the number of function evaluations required, in reducing sensitivity to starting point or seed variability, and in mitigating the effects of nonsmooth response variations.