

## MODEL REDUCTION IN MULTI-OBJECTIVE AND ROBUST DESIGN OPTIMIZATION

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#### **Optimizations of Expensive Numerical Model**

For many complex real-world design optimization problems, the numerical model in the design can be computational expensive , e.g. for the design optimization with Computational Fluid Dynamics (CFD), it may take hours for the computationally expensive model to evaluate an engineering design.

To tackle the issues due to expensive numerical model in the design, the low fidelity and cheap model can be used to guide the search. The low fidelity model can be the first order approximation to the expensive model, or th numerical model with coarse meshes. Another method is to use the surrogate, e.g. Kriging/Co-Kriging to reduce the cost.

Such methods works well in a series of test functions. However, one needs numbers of sample data to train the surrogate and the number of samples increases exponentially with number of design variables. One also need some extra sample points as the infill points to update the surrogate during the optimization. Therefore, the number of design variables of surrogate assisted optimization is strictly limited. In most of the literatures on surrogate assisted MOO, the number of design variables are no more than 10.

### **Optimization under Uncertainty**

In preliminary design, one also needs to analyze the impacts due to uncertainties. The uncertainties can be either aleatory or epistemic uncertainties. As for the aleatory uncertainties, their distribution information can be known and given prior to the design optimization. One can use the model, such as Gaussian distribution function to model the uncertainty impacts. However, such information can not be available for the epistemic uncertainties, particularly in the preliminary design. In this case, information of the uncertainties are given in some other forms, e.g. Basic Probability Assignment (BPA) structure. Two measures of the evidence, belief and plausibility can be used to measure the uncertain impacts. The belief measures the minimum or necessary support whereas plausibility reflects the maximum or potential support for that hypothesis.



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To evaluate uncertain impacts, one needs to explore the uncertainty space and design space. The cost can be huge and soon becomes prohibitive if numbers of uncertainties and design variables are involved. This lead to another problem: evidence approximation in the design optimization.

# Model Reduction in Multi-objective Optimization and Robust Design Optimization

The design optimization under uncertainty are commonly found in many practical problems, particularly in aerospace engineering design. With model reduction, e.g. Proper Orthogonal Decomposition (POD, also called Principal Components Analysis, PCA) based model reduction, expenses of searching process can be greatly reduced. Take the standard ZDT series test functions for example, it takes around 20 iterations for the MOO with POD model reduction to search the true Pareto front.

The model reduction can also be used in surrogate assisted optimization and evidence approximation. With model reduction, surrogate and evidence computation can be constructed on a reduced data set, thus the sample size can be greatly reduced.

The optimization with model reduction shows advantages over conventional MOOs and can be potentially extended to the scenarios such as optimization problems with many objectives. However, to implement successfully the methods in design optimization with expensive model under uncertainty, a series of issues such as evidence approximation, model fidelity management, optimization algorithm and the strategy to integrate them, etc. should be resolved. We therefore propose the special issue on Model Reduction in Multiobjective and Robust Optimization.

### Topics

- Multi-objective optimization
- Many-objective optimization
- Robust design optimization
- Multi-Fidelity optimization
- Uncertainty modeling
- Parameter reduction
- Data mining in Multi-objective and Many-objective Optimization
- Model fidelity management
- Surrogate of expensive model
- Model reduction in Multi-objective and Many-objective Optimization
- Infill strategy of surrogate



- Surrogate assisted optimization
- Evidence approximation of epistemic uncertainty
- Multi-objective robust optimization under uncertainty
- Applications of design optimization with model reduction, particularly the aerospace engineering design
- Preliminary space mission design under uncertainty
- Multi-objective optimization in preliminary space mission design