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An Efficient Robust Optimization Framework for Real-World Engineering Design

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ABSTRACT

Conventional design optimization can be described as the problem of determining the inputs (design variables $\boldsymbol{x}$) of an objective function $f(\boldsymbol{x})$ that will maximize or minimize its value at a certain design condition. Although the deterministic optimization that considers only the *optimality* of design (i.e. performance at design condition) should work fine in a controlled environment, real-world applications inevitably involve errors and uncertainties (be it in the design process, manufacturing process, and/or operating conditions); so that the resulting performance may be lower than expected. More recently, "robust optimization" that considers not only optimality but also *robustness* (i.e. performance sensitivity against errors and uncertainties) has attracted considerable attention in the search for more practical designs.

However, robust optimization requires further considerations when applied to real-world design problems. One major issue is that robust optimization is considerably more time-consuming than deterministic optimization. This is mainly because robust optimization requires evaluation of objective functions at many sample points around each searching point, in order to derive statistical values (*e.g.* mean value μ_f and standard deviation σ_f) which are then used as optimality and robustness measures for each objective function $f(\boldsymbol{x})$. Therefore, it is required to reduce function evaluation time for a more efficient robust optimization, especially in real-world design problems which utilize expensive computations for function evaluations.

Another important issue for robust optimization is the difficulty in interpreting complicated output data in order to obtain general design information. As mentioned above, robust optimization deals with twice as many objective functions as deterministic optimization, and the resulting high-dimensional output data (large number of objective functions) is rather complicated to understand and to discuss. The situation goes increasingly severe according to the number of objective functions involved, and thus, automated data analysis techniques are required to handle the large amounts of high-dimensional output data, and to reduce human load in real-world design problems which consider a large number of objective functions.

To solve the above issues, this study has proposed a new framework of robust optimization, as shown in Fig. 1. The first block constructs the response surface (RS), which approximates a *real* objective function $f(\boldsymbol{x})$ using a simple algebraic function, thus it enables an optimizer to promptly *estimate* function values. The Kriging model [1] is used here for RS construction, because it can adapt well to nonlinear functions. Based on the constructed RS, the next block searches for non-dominated solutions between optimality and robustness measures (μ_f and σ_f) through the optimization using the multi-objective evolutionary algorithm (MOEA) [2]. Those measures are estimated from the sampled $f(\boldsymbol{x})$ at many points around each solution. The final block applies the data-mining (DM) technique to the obtained solutions with many objectives, and extracts important information which is beneficial to optimality and robustness improvements. This framework uses the self-organizing map (SOM) [3] for the DM, because it can visualize indistinct patterns, which exist in high-dimensional data, in the form of simple two-dimensional maps.

This framework has been applied to an automobile tire design problem. This problem aims to find good design candidates regarding optimality and robustness of tire stiffness, when tire internal pressure disperses randomly around the nominal condition. Consequently, within a dramatically-reduced computational time, the present framework successfully found a *sweet-spot* design candidate, whose stiffness is better (larger) at the nominal pressure and less sensitive to the pressure dispersion than the baseline design (see Fig. 2).

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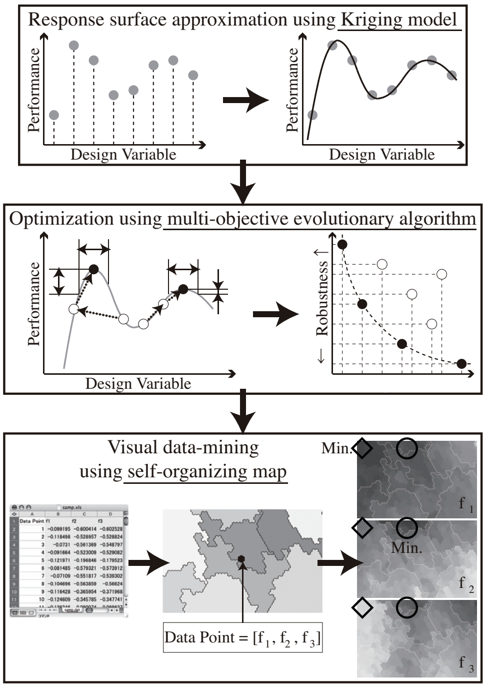

Figure 1: Robust optimization process

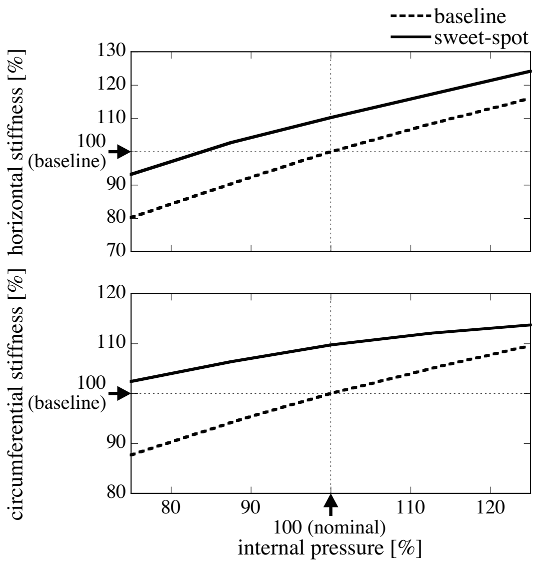

Figure 2: Obtained sweet-spot design candidate