Considering the Scatter of Fixed and Free Parameters in Optimization

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1 Introduction

When doing optimization in engineering, it is inevitable to check, whether the real scatter of manufactured parts has any influence on the reliability or robustness of the design proposed by the study. As especially bionic optimization includes stochastic approaches by its very definition [1, 2] these methods are easily expanded to include this check. Unfortunately stochastic thinking is not always applied to the data entering the optimization process in the everyday engineering work. We know that the variable optimization parameters and the design data defining the problem show some scatter. Consequently we have to take into account the varying optimization parameters and the scatter of the fixed non-optimization data during the optimization process. To come up with realistic guesses about the parts responses it is essential to make realistic estimates about the scatter and the corresponding distributions of all the input data of the optimization history.

2 Influence of scatter

This range or scatter may be small, if we think of measures like lengths, which are the result of manufacturing processes by high precision tooling machinery. Other data like material strengths, friction coefficients, contact areas or forces transmitted by screws are known with far less precision. A common and often-applied method of handling this uncertainty is to use the weakest value, hoping that this is a conservative assumption. Others use both the weakest and the strongest data to cover the region of possible results.

3 Interaction between parts

Especially if there are many components or parts interacting, this choosing of weak or extreme parameters does not always lead to proposals that correspond to realistic predictions of the structure’s response. For example we may model substructures with a relatively small stiffness. This weak stiffness yields a load distribution that underestimates the loads of the really endangered components. In consequence the scatter of all the system parameters that are not known to a very exact value should be taken into account using a sufficient coverage of the ranges of all variables.
Using this approach implies that the number of parameters will necessarily increase to relatively large numbers. The chance to find good or at least acceptable proposals decreases, as the high dimensional space of the scattering data has the potential to hide good or acceptable proposals. We often call this phenomenon the curse of the dimension. So there is the real danger not to find a sufficiently good design for the optimization project within an acceptable time.

4 Acceleration of the process

To come up with acceptable numbers of jobs for a robust and reliable optimization, accelerating strategies have to be found. An important class of these strategies are based on the fact that in stochastic processes not all parameters have the same impact on the object. So the reduction of the number of parameters to be handled may help to reach regions quickly where good values of the objective may be expected. A following local search may come up with acceptable designs in a relative short time.

Other strategies use statistical predictions to estimate the best values of the objective in the early stages. From such estimates we might derive decisions whether a region is promising. It is not surprising that these predictions again need large numbers of runs to yield reliable data measured in terms of the required reliability or robustness.

Checking the robustness of a predefined design requires many repetitions of the evaluation of the objective too [3, 4]. Once more, stochastic approaches may help to come up with accelerated indications of the sufficient reliability of the optimum design. In some cases deterministic studies may be even more efficient. One of the most popular approaches used in this regime consists of a transformation of all random variables to normal distributed ones. This transformation is often called the Rosenblatt transformation [5]. Unfortunately this Rosenblatt transformation especially in conjunction with methods simplifying the handling of the constraints has the property to be non-conservative in some cases. On the other hand it may produce results that are overly conservative. So the predicted qualities are far worse than the realistic ones.

5 Discussion of the efficiency

Proposals to come up with this back draws may be based on the use of more realistic distributions of the random variables. In some cases, especially if these distributions are of limited spread essential improvements of the predictions may result.

Such proposals may help to carry out robust and reliable optimization studies much faster than the methods used in general. Nevertheless optimization especially bionic optimization in the presence of many local optima remains a time and computing power consuming task. Furthermore any deterministic upgrading of stochastic processes has the potential reduce the validity of the probabilistic methods as it hurts the basic assumptions of probability theory. Non-valid statements may follow if these preconditions for the application of the probability theory, e.g. the independence of the random variables may be violated. In consequence a critical review of all input and all results becomes more important, even more repetitions may be necessary. Nevertheless an accelerated reliable and robust optimization may be a tool to find promising proposals at acceptable times and costs.

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