MULTICRITERIA, DISCRETE AND FUZZY DESIGN OPTIMIZATION IN EARLY DESIGN CONFIGURATION PHASES

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1. INTRODUCTION

Generally design optimization is used in the final phase of product design, when the overall configuration has already been defined in earlier development phases. To utilize the potential of a design in an optimal way, it is preferable to expand optimization to early design stages where also the configuration of the system under consideration is to be optimized. This often leads to discrete, multiscale and combinatorial tasks for the optimal topology of components, their dimensioning and their materials to be selected as well. This means the consideration of

- topology, geometry and material of the basic geometric and structural components
- proper placement of components and equipment
- multiple criteria, constraints and design parameters giving rise to multi-disciplinary interaction
- consideration of a certain fuzziness in requirements (constraints) including qualitative statements and (at least partly) lack of precise models

So the engineering team shall be supplied with a set of feasible and at least close to optimal configurations satisfying the main requirements. These then can serve as good starting points for further detailed optimization in next design steps.

In this paper the approach for a set of conceptual design optimization methods will be presented, which have been investigated and applied at the Institute of Lightweight Structures (LLB) of TU Munich. In addition, some specific aspects are discussed regarding discrete-continuous design optimization tasks especially in configuration as well as regarding possibilities to include fuzzy and qualitative knowledge into the optimization models. Our experience with modeFRONTIER follows and different demonstration examples will be presented at the end.

2. OVERVIEW OF THE APPROACH

At LLB an optimization system has been established which is composed of the following basic elements (see also FIGURE 1):

- An application management system (MOSES), guiding through the automated conceptual design process, keeping the optimization database and controlling the execution of the different software tools, as well as the parallel software execution on a computer cluster.
- A genetic optimization algorithm (GAME) capable of handling disjunctive and “rugged” design spaces.
- A CAD tool for appropriate geometrical description, re-presentation and para-meterization.
- the parameterized simulation models, eventually ranging from closed form solutions over response surface approximations, fuzzy logic models to finite element and/or finite difference methods

These elements are discussed in more detail in the following.
2.1. Application Management System – MOSES

In a typical configuration design optimization task one has to deal with different disciplines, models and software tools. Therefore an important aspect for the realization of multidisciplinary design is the integration of discipline specific software codes into a common analysis and optimization environment.

This is done by a so called application management system, which controls the data flow, job administration and execution process. It also provides tools for optimization, approximations and visualization. At LLB such application management functionalities have been implemented into the code MOSES (Multidisciplinary Optimization of Structures and Electro-mechanical Systems; FIGURE 1), which mainly builds upon the numerical analysis language MATLAB. MATLAB provides a flexible environment for numerical analyses per se and also the integration of other software tools and for implementing own algorithms. Because of the very different nature and problem structure of different design optimization cases, the management and process flow has to be flexible and adjustable with a rather loose coupling of different tools. The integration of various CAD tools (Catia, Pro/Engineer), finite element software (Ansys, Nastran) as well as own algorithms running under different software platforms (Windows, Linux, UNIX) on a computer cluster has been successfully managed.

![FIGURE 1: Application Management](image)

2.2. Genetic Algorithm – GAME

Configuration design problems like those addressed in the next chapter are typically characterized by a combination of continuous design parameters (e.g. dimensions) and discrete ones (e.g. selection of certain components or materials out of a discrete set), eventually also leading to disjoint design spaces. Additionally, these kinds of problems are often multi-criteria and multidisciplinary tasks. Moreover, the mix of different types of models and constraints leads to weakly structured problems where gradients for response quantities w.r.t. design variables are difficult to obtain. Because of this weakly structured problem an evolutionary algorithm GAME (genetic algorithm for multicriteria engineering) has been developed and implemented into MOSES.

The general flow chart of GAME is shown in FIGURE 2 on the next page. In addition to standard evolutionary algorithms GAME has special adaptation for multiobjective optimization and can handle continuous and discrete design parameters. It also provides response surface approximation (RSA) functionalities (see also 2.3.2 and [1]) and introduces competing subpopulations with adaptive evolutionary operators.

A drawback of evolutionary algorithms is their often high number of function evaluations. Especially when being close to constraint limits, these evaluations might quite often belong to infeasible designs. Such problems have been efficiently addressed by parallelizing the fitness function evaluation on a Beowulf cluster. The integration of response surface functionalities and competing sub-populations also increase computational efficiency and handling of large number of constraints.
FIGURE 2: Flowchart of evolutionary algorithm GAME including response surface approximations

2.3. Special features

2.3.1. CAD Integration

From the beginning of the process, geometric properties of the design and their manipulation (e.g. determination of c.o.g., probable collision etc.) are handled via CAD packages. Special control routines and interface packages developed at LLB for CatiaV5 and Pro/Engineer allow algorithmically triggered modifications of geometrical parameters or positions of components inside a CAD product assembly. If needed, the calculation of geometrical properties or the derivations of FEM models for mechanical analyses are carried out as well. This process is also controlled by the MOSES application manager.

The software interface with CatiaV5 is developed in CatiaV5’s own Visual Basic language. This interface is able to read in the geometrical design variables, to regenerate an updated CAD model and to provide the user with data of this new model, e.g. about mass, inertia moments and components interference. This interface makes it possible to use any existing CatiaV5 model in an optimization process. The amount of details in this model is only restricted by computer memory limits or, mostly, by the Catia calculation time the user finds acceptable in an extensive and complex configuration optimization task.

So the CAD tools such as CatiaV5 are controlled by the superior application management and optimization process and thus can be seen also as kind of sub packages within the overall CAE based process.

2.3.2. Response surface approximations

Response surface techniques are based on multiple design points respectively response values. The construction of response surface models is an iterative process. One starts with postulating the approximate model functions. These functions are constructed via linear, quadratic or higher order polynomials, eventually including certain functional relationships derived from knowledge and insight. For this, the designer has to know which variables of the optimization problem pay a role and which form is suitable to describe the relation between design variables and responses. Usually one starts with simple models like second order polynomials:

\[ \hat{y} = a + \sum_{i} b_i x_i + \sum_{i,j} c_{ij} x_i x_j \]

The coefficients \(a\), \(b\) and \(c\) are estimated by means of a least-squares algorithm. The required number of response values and therefore the number of (numerical) experiments grows up exponentially with the number of design variables.

For average size problems this should be manageable, especially when parallel processing is utilized. The selection of design points for determining the response values pays a great role. With different statistical methods especially the “design of experiments (DOE)” one is able to utilize procedural criteria beside
At the LLB response surface techniques are used for two main purposes. First of all they improve our genetic algorithm GAME. During an optimization run with a population based algorithm like evolutionary algorithms an enormous number of design points is evaluated, collecting a lot of information about the design space. The basic idea of integrating RSA functionalities in GAME is to increase efficiency by further exploiting this information by means of response surface approximations. Instead of using e.g. design of experiments methods for selecting the design points to build up the RSA. Here the population being already at hand is used. Because RSA can only be set up for continuous or quasi-continuous design variables, the population has to be split in subsets with consistent discrete variables before RSA methods can be applied. Depending on the size of these subsets linear, quadratic or mixed quadratic polynomials are used. First it is tried to set up the RSA over the whole design space. If this produces RSAs with not sufficient accuracy, a process is run that looks for subspaces where individuals form clusters (i.e. groups of closely or more closely packed individuals) on which it is more likely to built a RSA with sufficient quality. If this also fails, the RSA process is quit for this subset.

The process is set up in parallel to the EA process as shown in FIGURE 2. Once the RSA is set up, a gradient based optimization is run on the RSA. The optimal solutions found are then fed back into the population. This is a robust process because the optima found by the RSA optimization still have to prove their quality during the further evolution process. This compensates for poor optima due to low quality RSA or numerically failed optimization.

Secondly RSA is used to provide a global approximation of certain response values within the boundaries of the design variables. Depending on the problem less time consuming numerical evaluations are necessary to determine areas in the design space with optima using first a DEO-approach and then in a much smaller region exact numerical experiments. Noisy response is smoothed by using RSA. This avoids convergence problems induced by the suggestion of many local optima (FIGURE 3). Obvious advantage of such RSA is the explicit representation allowing very fast numerical evaluation over a wide area in the design space.

![FIGURE 3: shape of F_{Tail/Ws} -criteria over two design variables for high speed CFRP-rotor (left) and RSA approximation (right)](image-url)

To improve the performance of the models, expanded approximate model functions can be chosen (see also [2])

\[
\hat{y}(x) = \sum b_i h_i(x) = b^T h(x)
\]

\[
h(x) = [h_1(x), h_2(x), \ldots, h_{nk}(x)]^T
\]

With

\[
h_i(x) = \prod_{j=1}^{n_j} x_j^{\alpha_{ij}}
\]
\[ h_1(x) = e^{a_{11}x} \]
\[ h_2(x) = \ln(\alpha_{11}^T x) \]
\[ h_3(x) = \sin(\alpha_{11}^T x) \]
\[ h_4(x) = \cos(\alpha_{11}^T x) \]

\( \alpha \) is a parameter vector. It is important to generate some of the approximate model functions with prior knowledge of physic coherences, but the variety of possible model functions makes it necessary to provide the user with a strategy for choosing the other functions \( h \) and parameters \( \alpha \). For this, a MATLAB tool has been investigated and implemented at the LLB which divides the task into an inside (nonlinear) and outside (discrete) fitting problem. The inside fitting problem determines the optimal coefficients \( \alpha \) and the outside fitting problem the model functions \( h \).

3. **Completeness of Models and Inclusion of Fuzzy and Qualitative Knowledge**

One of the most important points for optimization is the completeness of the model. All relevant constraints related to functional, physical and technical requirements have to be considered. So called design model templates, which are based on prior experience, insight into the problem and its (potentially relevant) constraints, can be established in order not to lose sight of relevant constraints.

In early design stages a lot of information is not available in a crisp manner. Especially if some new techniques (e.g. for manufacturing) will be developed and tested during the project, which means that data from detailed models or tests are not available for preliminary design optimization. On the other side, often qualitative, fuzzy knowledge is available from experts which could be transferred into the modelling process. Not only one value can be vague (“x is roughly...”) but also the relations between some variables (“if x is roughly high and y is high then z will be approximately low”). Unlike Boolean Logic the antecedent is allowed to be partially true to some degree resulting in the consequent to be also partially true to some degree. The representation of such variables and rules in fuzzy logic is very similar to natural language and therefore very well suited to integrate human knowledge.

We want to illustrate the possibilities of fuzzy logic in the field of manufacturing and design optimization. There are three main applications. The first one is called ‘decision making’. The appropriate manufacturing method (and maybe the manufacturing parameters) are chosen by an expert system which needs a data base of all manufacturing methods to be considered. Information from established manufacturing methods (tests, handbooks... [3]) can be used, but it is difficult to compare new technologies with similar detail, because the lack of information as mentioned before.

The second application is the rating of suitability of a part or joint for a certain manufacturing method. Mainly linguistic rating is used, like “bad”, “middle” and “good”. This can be done with different levels of detail. For a part optimization the number of different criteria depends on the manufacturing method [4]. In FIGURE 4 the applicability for extrusion moulding of an aluminium hollow profile is plotted against the outer diameter and the ratio between the inner diameter and the outer diameter of the profile.

The third application is the modelling of rough values with fuzzy logic. For example mechanical properties or costs depending on design variables are of interest. Often only expert knowledge is available for such approximations [5].

The second and third applications are investigated in terms of design optimization at the LLB. By this
technique, at least rough and fuzzy approximations of relevant quantities as a function of at least some major design variables can be included in the design optimization model which otherwise would have been not considered. While single input – single output relations are conveniently handled, more effort has to be spent in the case of multiple inputs/parameters being relevant for a certain response quantity.

4. modeFRONTIER

modeFRONTIER is a very interesting multidisciplinary design optimization tool for our institute. The visualization makes it easy to understand the structure of an optimization and to present the results. Also the number of algorithms and approximation functions is impressive.

We accomplished some smaller tasks on a single computer and one of them was to implement GAME as optimization algorithm. We created a fake input which switches between two paths (FIGURE 5). The first path is used to start GAME through the MATLAB-interface of modeFRONTIER. GAME creates an output file for each individual of the optimization. Then we switch to the second path. Now modeFRONTIER reads the results from the output files and stores them in its own database for post processing. Unfortunately we loose the good visualization of the optimization process with this method.

The LLB (and most of the other research institutes) puts effort into some parts of the whole optimization process, like the algorithms. The other parts (e.g. input and output mask, flowcharts, etc.) are neglected. Therefore a modular program that provides the whole optimization process and allows changing some of its modules could be very helpful, because we could change just our part of interest. Interfaces to different programming languages could also provide a great flexibility. Such a modular configuration could give modeFRONTIER an advantage for use at research institutes.

5. APPLICATIONS

In the following, two different applications are discussed in order to show the flexibility and general scope of the selected approaches.

5.1. Geometrical Configuration Optimization of a Satellite Bus

In early development stages of satellites, the major components derived from customer and system requirements have to be transferred to a proper geometrical-mechanical configuration. This configuration process includes the equipment arrangement as well as the selection of the overall geometrical and mechanical parameters.

Since the definition of a geometrical-physical configuration of satellites is a highly complex task which not easily lends to computerization, a proper decomposition into better treatable problems is in order. The solutions of these then have to be synthesized on system level. First steps in this direction have been done
for the GAMMA-bus (FIGURE 6), which to a considerable extent is representative for a large quantity of medium-sized (constellation) satellites. GAMMA contains all relevant subsystems and configuration processing elements, and so is used as reference and benchmarking configuration.

The main equipment of GammaBus consists of over 50 single components. A configuration task has been set up to locate the optimal positions of these components, with respect to c.o.g constraints, collisions constraints as well as functional constraints, e.g. for the assembly of momentum wheels. Each component can be positioned on one of the four side panels or on the top panel.

The generic CAD-model (CatiaV5) has been implemented in the optimization run for representing the geometry for the main structural components as well as for each equipment component; further, CatiaV5 helps calculating the geometrical properties of each individual configuration, e.g. collisions between equipment components, inertia moments or c.o.g.

Due to the CAD-model size of GammaBus, the process of equipment positioning and calculating geometrical properties (for one single configuration) requires about 2-3 min on a PC (depending on the processor and memory of the PC). In combination with the large number of single analyses, which are typical for configuration problems tackled by a genetic algorithm, this leads to high computational effort. For this example about 10000 different payload configurations have been analyzed by CatiaV5 on a 20 PC computer cluster with a total computing time of nearly 24 hours.

The configuration process is as follows: for computer generated configuration definition, a two step approach has been selected:

1) Placement of subsystems and equipment via a genetic algorithm under consideration of functionality and integratebility (e.g. equipment belonging to a subsystem shall be placed onto the same panel / close to each other), position of centre of gravity, field of view, as well as design rules

2) Stiffness and load carrying optimization of required structure via genetic and mathematical optimization algorithms

At the beginning of configuration design the process is mainly determined by the high dimensionality and complexity of geometrical design space. Therefore as a first step the geometric constraints have to be satisfied, while in the second step the geometrical feasible configurations together with structural parameters are optimized.

Results of the first configuration step carried out for the GammaBus payload bay are shown in FIGURE 7. The position of the centre of gravity as well as functional constraints is maintained. Only a slight overlap between two components exists in this solution due to not properly set (discrete) position variables.
In the second step a combined structural-geometrical optimization (including FE-analysis) is established to find best tradeoffs between component placing and structural design. In this step also different materials can be taken into account as well as various competing structural designs, e.g. different tank supporting structures. A result of such an optimization task is shown in FIGURE 8, where three different pareto-curves (mass vs. stiffness) are shown for three different tank supporting structures.

FIGURE 8: Comparative Pareto Rankings for the three Tank Supporting Structures in GammaBus

5.2. Optimization of an reinforced aluminium I-section beam with manufacturing constraints

The manufacturing of extrusion moulded aluminium or magnesium profiles, which are reinforced with wires, has the advantage of an increased ultimate strength and stiffness. But the reinforcing elements increase also the cost.

The aim of the optimization was to maximise the specific bending stiffness and simultaneously minimise the cost of a reinforced I-section beam compared to a reference profile made of aluminium without reinforcement. Only material costs were considered.

Two manufacturing constraints concerning the minimum wall thicknesses proportional to the diameter of the reinforcing elements were included via expert knowledge. Also the absolute bending stiffness had to be higher then the one of the reference profile. The design variables included the matrix material (aluminium, magnesium), the reinforcement material (steel, carbon fibres), the number of reinforcing elements and the geometric dimensions of the I-section (FIGURE 9).
The results can be seen in FIGURE 10. In the lower left corner aluminium – steel combinations didn’t provide a considerable increase in specific strength. Aluminium – carbon fibre has a wide range of possible combinations and magnesium – carbon fibre is at the upper right corner of the chart, which stands for the highest gain in specific bending stiffness but also the highest increase in cost.

In this optimization a lot of manufacturing constraints were not considered. For example the influence of material combinations (micromechanics) and the restrictions of the extrusion press (number of reinforcing elements, minimum wall thickness for extrusion...). Also the accounted restrictions are not prepared for a design optimization of a whole structure yet, because these values vary with different dimensions of the profiles. This is the area where RSA and fuzzy logic will be used in the future, especially because the extrusion process of reinforced profiles is now under investigation and only expert knowledge is available for some influences.

6. CONCLUSION/ACKNOWLEDGEMENT

The chosen approach has been proved to be quite flexible for covering different design optimization problems in earlier design stages. In addition to steady improvements in generality and numerical efficiency of the different algorithms involved, future focus will be onto the inclusion of fuzzy requirements and knowledge, which will further improve quality, consistency and completeness of optimization. This will also make possible to include at least some aspects of manufacturing (and cost) in early design phases.

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References


