Reduction Process of Weight for Folding Stroller by Goal Driven Optimization

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ABSTRACT

In this titled paper the optimization of a stroller components in computer aided design (CAD)-based on a structural optimization problem. A methodology for the efficient solution of the corresponding design optimization problems is presented. Each design criterion as well as the constraints imposed on the design variables and problem parameters are characterized by preference functions. High-quality approximations for the system response functions are constructed using the concepts of intermediate response quantities and intermediate variables. And simulation also tries to extract the relationship of deformation, mass and other design parameters by the deterministic method through sensitivities and response. Application programs developed to integrate commercially available CAD/CAM/FEA/Design optimization tools enable implementation in virtual environment and facilitate automation. The application programs can be reused for similar design problems provided that the same set of tools is used. In case of solution method sensitivity analysis were also conducted.

Keywords: Computer aided design (CAD), Design Variables, Responses function, System Response, Intermediate variables.

1. Introduction

With the advent of ever faster computing platforms, computer aided numerical optimization and simulation tools are becoming more attractive for the design of engineering systems. The application of these computational tools allows a more rapid design process and more detailed design studies. In recent years, optimization based design methodologies have been applied to a broad range of engineering design problems, for example, in structural, fluid, and thermo-mechanics [1-5].

Currently, design optimization methodologies are extended into coupled field problems, such as thermo mechanical coupling and fluid-structure interaction [6-10], including design under uncertainties [11-13]. While the complexity of the systems being optimized is increasing, which requires ever more sophisticated computational techniques, a fundamental bottleneck in the computer aided optimization procedure still remains: the formulation of the optimization problem itself. In the case of realistic design problems, the formulation of an optimization problem, whose final solution satisfies all practical requirements, is a challenging and time-consuming issue, requiring a substantial amount of expertise and experience. These difficulties can be subdivided into two subtasks: the definition of the optimization variables and the formulation of the objective and constraints.

Defining optimization variables is in particular a complex task in optimization using a CAD-type representation, such as solid modeling or the design element concept [14-15]. Building a so-called design model [16] requires the identification of optimization variables, such as the position of spline control nodes, and their upper and lower bounds, which need to be chosen such that all potential configurations yield valid geometries, i.e. there is no penetration or overlapping of surfaces. In addition, shape variations often need to be restricted to geometries satisfying manufacturing or assembly requirements. This task is particularly cumbersome if the shape of three-dimensional structures is optimized. Different approaches have been proposed to automatically generate and/or refine the design model [17-19].

This study is primarily concerned with the second aspect of the above mentioned bottleneck, namely the formulation of the objective and constraints. This task can be essentially broken down into two steps: (A) the selection of design criteria being considered and (B) the composition of these criteria into an objective function and constraints. The latter step is an essential problem for the formulation of multi-objective optimization problems [20-21].

In case of the practical design problems, the selection of the design criteria always creates serious difficulties. Typically, the engineer starts with an initial formulation of the design problem, which then can be solved by an appropriate optimization technique of choice. Often, the solution of the initial formulation does not satisfy the expectations of the engineer on the final design and a slightly different design is desired. However, these alterations may violate some design constraints. The reasons for this shortcoming are twofold: (A) The engineer did not or was not able to specify all design criteria that are needed to obtain a result with desired characteristics; and/or (B) the formulation of the objective function composed of the specified criteria was not appropriate or some cases inaccurate. Therefore, the optimization problem needs to be reformulated such
that the desired shape can be obtained as nearly as possible, without violating any constraints.

In this paper, a practical approach is presented for the automatic reformulation of an optimization problem in terms of objective and constraints. The goal of this approach is to assist the user of a computer based design optimization tool in selecting the design criteria and formulating the optimization problem that leads to the desired design. The design criteria are identified and the formulation of the optimization problem is adapted based on the engineer’s modifications to an existing, potentially optimized design. The main benefits of this approach are twofold: (A) The engineer obtains the design problem understanding which insights the physical criteria are dominating the design with desired characteristics; and (B) the interactive modification results in an infeasible design, the design criteria that have been identified can be added to the problem statement and the updated optimization problem can be solved, leading to a feasible design that is the best possible approximation of the desired design. The proposed approach is embedded into an interactive design process allowing for the iterative interaction between the engineer and the optimization tool (see Fig. 1). This procedure will be illustrated by goal driven optimization problems, but is applicable to other disciplines as well.

The remaining sections of this paper are organized as follows: In Section 2 the main ideas behind the proposed reformulation of the optimization problem are presented. In Section 2.1 the mathematical properties of a nonlinear constrained optimization problem, which motivates the formulation of an optimization problem for identifying the design criteria, are summarized. In Section 3 the feasibility and the potential of the proposed method will be illustrated by showing the analysis and the curves and also by the model of the optimization problems. And also in this section the main basics of the Goal Driven optimization is discussed & showed by the variables and its summarization. The features of the presented approach are summarized and future extensions are discussed in Section 4.

2. Sequential Reformulation of Optimization Problem
A typical design optimization problem for this process can be defined as follows:

Minimize \( \phi(b) \)
Subject to \( \psi_i(b) \leq \psi_i^u \) and \( b_j^l \leq b_j \leq b_j^u \)

(1)

Where \( \phi(b) \) is the objective function; \( b \) is the vector of design variables captured in CAD solid models; \( \psi_i(b) \) is the \( i^{th} \) structural performance measure with its corresponding upper bound; \( \psi_i^u \); and \( b_j^l \) and \( b_j^u \) are lower and upper bounds of the \( j^{th} \) design variables, respectively.

2.1 Non-linear constrained optimization
Assuming that the objective and constraints are sufficiently smooth functions of the optimization variables \( s \), the solution of the above constrained optimization problem is characterized by a stationary point of the following Lagrange function:

\[
L(s, \beta, \gamma) = f(s) + h(s)^T \beta + g(s)^T \gamma
\]

(2)

where \( \eta \) and \( \gamma \) are vectors of Lagrange multipliers. The Karush–Kuhn–Tucker (KKT) conditions are the first order necessary conditions for a local extremum:

\[
\nabla L = \nabla f(s) + \nabla h(s)^T \beta + \nabla g(s)^T \gamma = 0
\]

(3)

where \( \nabla \cdot \) is the gradient operator with respect to the optimization variables \( s \). In structural optimization, for example, the objective \( f \) and the constraints \( h \) and \( g \) are typically functions of certain optimization criteria, such as mass, strain energy or stress, which are in turn explicit or implicit functions of the optimization variables \( s \).

At the optimum, \( \nabla L \) vanishes. For non-optimal designs the norm of the residual together with the norm of the constraint violations can be used to measure the quality of the intermediate result.

3. Geometry Based Modeling
The solid modeling system used herein is based on geometric element modeling. This type of modeling is based on three main aspects: problem formulation through geometry, geometry representation and geometry manipulation.

The formulation of the shape optimization problem by using the geometry is depicted in Fig. 2. The process begins using solid design elements to define the problem geometry. Then, the mesh control information is defined on the boundary as well as the problem-specific attributes, such as material properties, loads, boundary conditions, etc., are assigned to the model.

Fig.1 Interactive process of goal driven optimization
4. Analysis of Numerical Sequential Process

Design objectives that can be used to measure design quality include minimum weight, and maximum deformation, as well as many others. Typically, the design is limited by constraints such as the choice of material, allowable strength and deformation, load cases, support conditions, and technical constraints (e.g., type and size of available structural members and cross-sections, etc.). Hence, one must decide which parameters can be modified during the optimization process; these parameters then become the optimization variables. Isotropic structures can usually be described by three different types of design variables: (1) sizing variables, (2) geometric variables, and (3) topological variables. Goal driven optimization is concerned with determining the cross-sectional size using a given geometry. Configuration optimization searches for a set of geometric and sizing variables using a given topology. Topology optimization selects from various structural types. In general, goal driven optimization is a combinatorial optimization problem.

4.1 Goal Driven Optimization of a Stroller:
Goal Driven Optimization (GDO) is a constrained, multi-objective optimization (MOO) technique in which the "best" possible designs are obtained from a sample set given the goals you set for parameters. The sample set is generated either by the Screening or Advanced option in the sample generation menu. Advanced sample generation can only be performed when all of the input parameters are continuous or uncertain.

The GDO process allows you to determine the effect on input parameters with certain preferences applied for the output parameters. For example, in a structural engineering design problem, you may want to determine which set of designs (in terms of geometric problem dimensions and material types) best satisfy minimum mass, shear strengths, and minimum cost, with maximum value constraints on the von Mises stress and maximum deformation.

4.2 Exact recovery of formulation of the goal driven optimization of Folding Stroller:
For strollers as the goal driven optimization algorithm is used. But first we settled down the optimization criterion/conditions:

Table 1 Optimization conditions for the Goal Driven optimization of a Folding Stroller:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Desired Value</th>
<th>Importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Directional Deformation</td>
<td>Less than 20.</td>
<td>Higher</td>
</tr>
<tr>
<td>Maximum</td>
<td>mm</td>
<td></td>
</tr>
<tr>
<td>Total Deformation</td>
<td>Minimum</td>
<td>Higher</td>
</tr>
<tr>
<td>Maximum</td>
<td>possible</td>
<td></td>
</tr>
<tr>
<td>Maximum</td>
<td>Less than 762.</td>
<td>Higher</td>
</tr>
<tr>
<td>Compressed Stress</td>
<td>Maximum</td>
<td></td>
</tr>
<tr>
<td>Maximum</td>
<td>MPa</td>
<td></td>
</tr>
<tr>
<td>Geometry Mass</td>
<td>Minimum</td>
<td>Higher</td>
</tr>
<tr>
<td></td>
<td>possible</td>
<td></td>
</tr>
</tbody>
</table>

4.2.1 Loading Conditions:
The loading conditions are basically divided into two categories. These are:

(Case1) To give the movement to the stroller
(Case2) To put the weights on the stroller
Table 2 Optimization and same diameter cases in case of goal driven optimization:

<table>
<thead>
<tr>
<th>Case</th>
<th>Same Dimension (mm)</th>
<th>Optimization Dimension (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tube1(In-r)</td>
<td>12</td>
<td>10</td>
</tr>
<tr>
<td>Tube1(out)</td>
<td>12</td>
<td>10.6</td>
</tr>
<tr>
<td>Tube2(In-r)</td>
<td>12</td>
<td>14</td>
</tr>
<tr>
<td>Tube2(out)</td>
<td>12</td>
<td>15.6</td>
</tr>
<tr>
<td>Tube3(In-r)</td>
<td>12</td>
<td>10</td>
</tr>
<tr>
<td>Tube3(out)</td>
<td>12</td>
<td>11.5</td>
</tr>
<tr>
<td>Tube4(In-r)</td>
<td>12</td>
<td>10</td>
</tr>
<tr>
<td>Tube4(out)</td>
<td>12</td>
<td>11.2</td>
</tr>
<tr>
<td>Tube5(In-r)</td>
<td>12</td>
<td>8</td>
</tr>
<tr>
<td>Tube5(out)</td>
<td>12</td>
<td>8.5</td>
</tr>
</tbody>
</table>

4.2.2 Optimization History:

Here in Fig. 6 we describe the optimization history of the selection of inner radius of the tubes in case of the parameter selection of the folding Stroller. This minimization of the structural history from the von mises theorem.
Here in Fig. 7 we describe the optimization history of the selection of outer radius of the tubes in case of the parameter selection of the folding Stroller. This minimization of the structural history from the von misses theorem. And this is also the optimal radius selection for the process of weight minimization.

Sensitivity analysis for selecting the tube radius of optimal value:

\[ \text{Fig. 8 Sensitivity analysis for tube radius selection} \]

4.2.3 Optimal Solution from Goal Driven Optimization: From the Goal Driven Optimization conditions it generates 3 choices as like the upper table. And candidate B gives the good result as our optimal goal is to lightening the weight. From our point of view lightening of the stroller achieved the ratings result by the use of the algorithm.

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<table>
<thead>
<tr>
<th>Parameter</th>
<th>Candidate A(mm)</th>
<th>Candidate B(mm)</th>
<th>Candidate C(mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tube 1(in-r)</td>
<td>10</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>Tube 1(out)</td>
<td>10.9</td>
<td>10.6</td>
<td>10.8</td>
</tr>
<tr>
<td>Tube 2(in-r)</td>
<td>14</td>
<td>14</td>
<td>14</td>
</tr>
<tr>
<td>Tube 2(out)</td>
<td>15.1</td>
<td>15.6</td>
<td>15.4</td>
</tr>
<tr>
<td>Tube 3(in-r)</td>
<td>10</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>Tube 3(out)</td>
<td>11.4</td>
<td>11.5</td>
<td>11.4</td>
</tr>
<tr>
<td>Tube 4(in-r)</td>
<td>10</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>Tube 4(out)</td>
<td>11.6</td>
<td>11.2</td>
<td>11.4</td>
</tr>
<tr>
<td>Tube 5(in-r)</td>
<td>8</td>
<td>8</td>
<td>8</td>
</tr>
<tr>
<td>Tube 5(out)</td>
<td>8.6</td>
<td>8.5</td>
<td>9.1</td>
</tr>
<tr>
<td>Deformation (mm)</td>
<td>1.6025e-002</td>
<td>1.8453e-002</td>
<td>5.1645e-002</td>
</tr>
<tr>
<td>Stress (MPa)</td>
<td>8.1025</td>
<td>7.3303</td>
<td>1.9264</td>
</tr>
<tr>
<td>Mass (Kg)</td>
<td>1.8251</td>
<td>1.7872</td>
<td>2.6757</td>
</tr>
</tbody>
</table>

5. Results

It is found that in case of our procedure we obtained the optimal dimensions for stroller by the GDO process and optimized mass and final shape. We also applied the sensitivity analysis to describe the feasibility of our proposed process and design. In case of this proposed model our weight is reduced 15%. In case of our testing procedure the baby we considered its age is 2.5 to 4 yrs.

6. Conclusion

Strollers are very important thing to our regular life now a day. Automated simulation based optimization procedures are an appealing approach to improving engineering designs while simultaneously reducing the turnaround time in the design procedure. This method is embedded into an interactive design procedure: an optimization tool generates an optimized design for a given optimization problem; this design is modified by the engineer to satisfy requirements that have not been explicitly formulated in the optimization problem; the proposed method identifies the design criteria that drive the user modification and formulates an adapted optimization problem that accounts for the user modification and can be used in a subsequent iteration step.

Now from all the analysis and apparent mass measurements and deformation measurements and overall the measurements of lightening with cohorts of subjects following conclusions can be drawn:

1) The presented approach is based on a template multi-criteria formulation of a generalized objective function and has been specified for the weighted-sum approach in case of the folding stroller. The vari
able weighting factors of the strollers are used to adapt the formulation of the objective function, such that the solution of the resulting optimization problem approximates a user modified design. The variables are adjusted by solving an inverse optimization problem.

2) The objective of this Stroller optimization problem is to minimize the residual of a subset of the KKT conditions at a design specified by the user. The optimization variables for the inverse problem are the variable parameters of the templated multi-criteria formulation of a generalized objective function.

The solution of the folding stroller optimization problem is computationally inexpensive since its objective and constraints are explicit functions.

REFERENCES