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EDA'S BASED APPROACH TO MULTIOBJECTIVE SHAPE OPTIMIZATION

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Summary. *We propose a new approach to solve shape optimization problems based on estimation of distribution algorithms (EDA's) combined with information from the physical problem (finite elements connectivities). Our algorithm improves exploration capacity by the regularization of the probability vectors. Therefore, the number of small holes in the structure is decreased as well as unconnected elements (elements connected at a vertex whose sides are not shared). We use a multiobjective approach to find Pareto solutions for two design goals: minimum weight and minimum displacement at some specific nodes. The solutions must fulfill three design constraints: maximum permissible Von Misses Stress, requirement of connectedness by sides in elements, and designs with small holes are not allowed.*

1 Introduction

The goal of this work is the multiobjective design of two-dimensional shapes for some load condition. Several authors have approached the shape optimization problem through the use of genetic algorihtms (GA) [3, 5, 4]. Their work have proved the GA's capacity to find approximate solutions, nonetheless, two problems have prevented them from complete success: the lack of a "good" function to model all desirable features of the design, and premature convergence due to the lost of diversity.

2 Problem Definition

The multiobjective design goal is to find the set of structures with minimum weight and node displacements, which fulfill three design constraints: maximum Von Misses stress, small holes, and unconnected elements in the structure (see Section 2.5).

2.1 Discretization and representation

A discrete form of the search space consisting of a given number of elements (in order to use the finite element method, see [9]) is used. Every element is represented by a bit in a binary array $\hat{x}$. If a bit value is 1 the corresponding element is present in the structure so it has thickness, otherwise it is one-element gap in the structure.

2.2 First Objective: Minimum Weigth

The first objective function is the minimum weight of the structure. It is calculated by Equation 1, where n is the number of elements, w_i is the weight of the $i-th$ element, and x_i is the bit value in the $i-th$ position of the binary array. The first objective is the following:

$$Minimize: \quad W(x) = \sum_{i=0}^{n} w_i x_i \tag{1}$$

2.3 Second Objective: Node Displacements

The second objective function is the displacement at some specific nodes (could be all of them). This objective is computed by Equation 2, where m is the number of nodes whose minimum displacement is required (normally the nodes with load), and δ_j is the displacement of the $j-th$ node.

$$Minimize: \quad G(\delta) = \sum_{j=0}^{m} |\delta_j| \tag{2}$$

2.4 First Constraint: Von Misses Stress

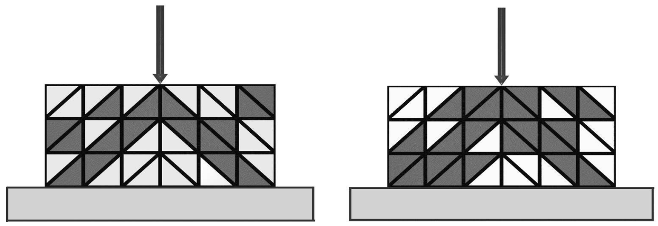
The first constraint is given by a maximum permissible Von Misses stress, therefore, every element in the structure must have less stress than the maximum permissible.

2.5 Second and Third Constraints: Connectedness and Small Holes

The connectedness constraint is measured by counting the number of objects in the structure; an object is a set of at least two elements with one common side. Then, the connectedness constraint requires 1-object configuration in the structure, Figure 1(a) shows a 4-object configuration. A "small hole" is a non-present (0 value) element whose surrounded neighbors are present. The small hole constraint is measured by counting the number of small holes in the structure, Figure 1(b) shows a 3-small hole configuration.

3 Outline of the Algorithm

First, we initialize the probability vectors $\hat{p}$. Then, every probability vector p_i generates a subset of the population. Finally, all the non-dominated feasible individuals and some infeasible individuals are taken to update the probability distributions (the *current Pareto set*). When the probability distributions have lost their exploration capacity, we run a procedure to regularize the probability vectors. At every generation the



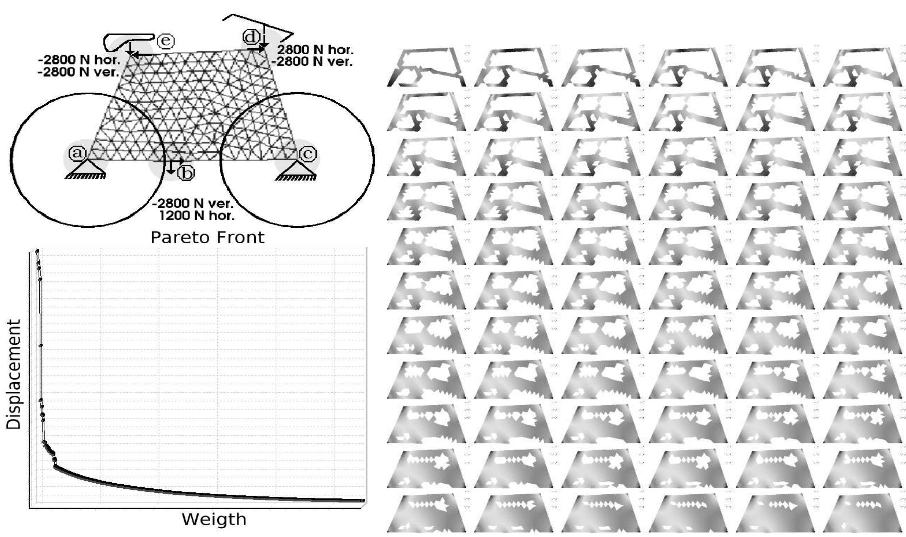
(a) **(b)**

Figure 1: (a) 4-Object configuration, (b) 3-small hole configuration

known Pareto set is updated to save the solutions (non-dominated and feasible individuals). More information about the algorithm can be found in [1].

4 Design problem

The problem is the design of a hypothetic bicycle frame. The non-dominated individuals and its corresponding structures (from a typical run) are shown in Figure 2. The displacement was minimized at the 3 load nodes. (The own weight is not considered as a load in the optimization problem).



(a) **(b)**

Figure 2: (a) Load condition and Pareto front of our design problem, (b) Some structures from any typical run

5 Conclusions

A new approach for multiobjective shape optimization based on EDAs and Pareto dominance as constraint handling mechanism was introduced. The presented results show a good behavior and optimal solutions despite the use of an unstructured mesh (most authors use a structured mesh). In future work we will explore how strong the optimization problem depends on the mesh, and how to initialize the probability distributions in a multigrid strategy that considers mesh dependency and search space reduction (after re-meshing the search space). Another issue that deserves analysis is the reduction of the computational cost by limiting the size of the Pareto set.

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