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Multi-objective weight and cost optimization of hybrid composite-concrete beams

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ABSTRACT

The construction industry currently shows an increasing interest towards composites. However, despite their high mechanical capacity to weight ratio their practical use in construction remains rather limited, the relatively high cost often being mentioned as the most restricting factor. This paper demonstrates how this need for minimization of both cost and mass can be tackled by a multi-objective optimization. First, a two-objective size optimization procedure is developed, and subsequently its strength is illustrated on hybrid composite-concrete beams. An original methodology combining Non-dominated Sorting Genetic Algorithm (NSGA-II) and a meta-model is used to find all optimal solutions. The optimization algorithm moreover gives insight on the influence of different parameters such as the span and the concrete class on the weight and cost of the beams, and the dominance of certain design constraints in various locations of the design space.

1. Introduction

Composite materials have gained a strong interest in different domains because of their interesting properties such as high mechanical strength, low weight, good durability, potential to tune the material to the application, etc. The use of composites in construction however is today still not widespread, with main applications limited to the repair and strengthening of existing structures, making use of FRPs (Fiber Reinforced Polymers) and TRCs (Textile Reinforced Cement) [1,2].

The main reason of this limited use of composites in construction is their relatively high cost. Indeed, contrarily to other sectors, in construction industry the design of structures often aims for cost reduction, at the expense of the weight. Composite structures are not competitive to traditional structures in many cases. However in applications where the lightweight aspect plays a prominent role, composites could prove their effectiveness. Important for the designer is thus to find a certain balance between mass and cost, leading directly to the definition of two design objectives. This design problem can be tackled by multi-objective optimization algorithms.

In literature, research can be found on the optimization of composite materials with weight, (manufacturing) cost and structural performance as most important objectives [3–7], yet this research is mainly done on the optimization of the composite laminate itself (i.e. fibre orientation).

In this paper we aim to develop a methodology to optimize hybrid composite-concrete beams, made out of multiple materials with very different cost/weight ratios, towards the two objectives of cost and mass, varying the geometry of the elements (i.e. element height, composite material thickness). The combination of concrete (low cost/high self-weight) with composites (high cost/low self-weight) results in opposite objectives. The specific issue in solving this kind of optimization problem is the calculation time of the structural analysis of the hybrid beams in every optimization iteration.

To reduce the calculation time, this paper develops a new methodology for optimizing structures combining a Non-dominated Sorting Genetic Algorithm (NSGA-II) [8] with a meta-model [9]. Before the optimization is performed, the meta-model is established by calculating the structural response of a limited number of structural geometries (with given variable values). Then, during the optimization, instead of soliciting the structural analysis module at every iteration, an interpolated solution is calculated using the meta-model, reducing significantly the calculation time. The Non-dominated Sorting Genetic Algorithm (NSGA-II) [8] results in a Pareto front which represents all non-dominated solutions, for which none of the objective functions (mass and cost) can be improved without degrading the other. All Pareto optimal solutions are sets of variables which allow the

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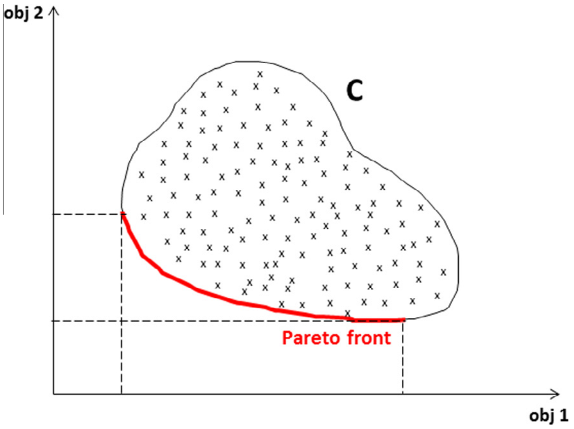

Fig. 1. The Pareto front is the set of all non-dominated solutions.

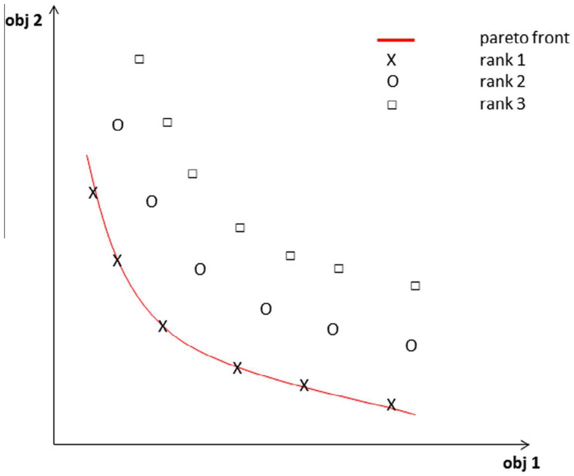

Fig. 2. Principle of NSGA-II: through non-dominating ranking the population moves to the Pareto front.

designer to decide which of these solutions is the most appropriate compromise between mass and cost for any given situation.

In a first step the optimization program is used to find the set of non-dominated solutions (the optimal cross-sections) of a 5 m span beam. Furthermore the program is used to perform a parameter study to verify the influence of different parameters such as span, concrete class and maximum allowed deflection.

2. Optimization procedure

This section describes the applied optimization methodology. First, the general problem definition of size-optimization is given, and the used optimization algorithm NSGA II is introduced. Then, the coupling between structural analysis and optimization is discussed. The introduction of a meta-model instead of the structural analysis module in the optimization routine to reduce the calculation time is explained.

2.1. Multi-objective optimization: principle

A size-optimization problem is defined to find the optimal cross-sectional dimensions of a structure that minimizes the objectives (mass and/or cost) and simultaneously meets all predefined constraints (e.g. maximum deflection). These constraints define the feasible solution space [10]. To tackle both the mass and the cost, a multi-objective optimization procedure is elaborated. Generally, constrained multi-objective optimization problems can be formulated as [11]:

$$\begin{array}{lll} & \min\limits_{x} f(x) & \textit{Objectives} \\ \text{such that :} & \left\{\begin{array}{l} g(x) \leqslant 0 \\ h(x) = 0 \\ x_i \in X_i \quad \text{for} \quad i = 1, \ldots, n \end{array}\right. & \begin{array}{l} \textit{Inequality constraints} \\ \textit{Equality constraints} \\ \textit{Variables} \end{array} \end{array} \tag{1}$$

By changing the variables the multi-objective optimization finds different solutions that minimize the objectives and fulfil the constraints. Contrarily to single-objective optimization, multi-objective optimization generally leads to multiple trade-off solutions. From all feasible solutions (Fig. 1, collection C) the set of non-dominated solutions –solutions for which at least one of the objective functions cannot be lowered without increasing the other(s)– are defined within the Pareto front (Fig. 1, red line). Since no single optimal solution exists, the user has to decide which solution of the Pareto front is the optimal solution for his particular problem, a so called “a posteriori” method [11].

2.2. NSGA-II

Several optimization algorithms exist to solve constrained multi-objective problems. The appropriate algorithm is chosen depending on the nature of the problem (design variables, size, local or global optimum, etc.). For this research genetic algorithms (GA’s) are used. GA’s imitate a biological evolution and differ from other conventional algorithms on three points [12]: (i) Randomized operators (mutation, selection and recombination) are used instead of the usual deterministic operators. (ii) Instead of working with a single design point they work with a population of design points. (iii) They can handle continuous, discrete or mixed variable optimization problems. Among the different existing GA’s NSGA-II (Non-dominated Sorting Genetic Algorithm) was chosen for this particular problem [8]. NSGA-II is a widespread a posteriori method to solve multi-criteria optimization problems. It is a popular method, especially for its robustness, and is used in plenty of (mechanical) engineering applications. Starting from an initial population, the Pareto front is found by ranking and selecting the individuals according to non-domination (Fig. 2). Different layers can be distinguished, having individuals with the same fitness

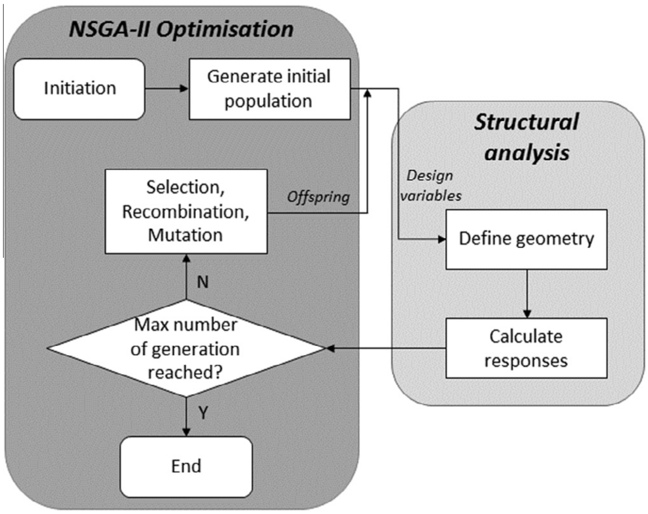

Fig. 3. Flow-chart.