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Multi-disciplinary optimization of building spatial designs

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Abstract

The global expenditure of resources may be significantly reduced by optimizing building designs, especially at an early stage. This paper presents three methods for early stage building spatial design and optimization: (I) an evolutionary algorithm, (II) a simulation of design processes, and (III) a hybridization of methods (I) and (II). Both methods (I) and (II) naturally show advantages and disadvantages, which have been analysed. Accordingly, it is shown that hybridization successfully combines both the methods and their advantages while their disadvantages are diminished, yielding a method that can find better results in a more efficient approach.

Keywords: Design process simulations, Evolutionary algorithms, Hybridization, Thermal Design, Structural Design, Design support systems.

1 Introduction

The built environment is responsible for 40% to 60% of the expenditure of resources in Europe. Minimizing this expenditure in building designs may thus have a significant impact. This is especially true for the early stages of a building design process. This paper therefore presents three methods for the design and optimization of building spatial designs: (I) an evolutionary algorithm, (II) a simulation of design processes, and (III) a hybridization of methods (I) and (II), which employs them in a sequential manner. The methods are employed to find building spatial designs that perform well for two objectives: (i) minimal strain energy, which is the internal energy due to displacements of the structural components that help realize a building spatial design, and (ii) minimal heating and cooling energy, which is the energy that is required to keep the indoor temperature of a building spatial design within a comfortable range.

Each method has been employed to find a building spatial design of 50 spaces with a floor surface area of 750 m^2. The objectives are evaluated using automatically generate structural finite element models and thermal resistor-capacitor networks. Method (I) is observed to find well distributed Pareto front approximations that can be used to learn about the design problem, which is not the case for method (II). On the other hand, method (II) can find better results than method (I), and faster. Method (III), the hybrid method, shows that it can find better results using less evaluations, while still providing distributed Pareto front approximations. As such, hybridization successfully combines methods (I) and (II) and their advantages, while their disadvantages are diminished.

The improvement that is achieved via hybridization can be related to the interactions between the problem and solution spaces, which is enabled by simulating design processes in method (II). As such, design processes have been used in this work to improve the performance of an optimization method. Future work will therefore focus on the integration of the presented methods into a design process, whereby the optimization methods can benefit from a design team, and a design team can benefit from suggestions that are made by the optimization methods.

2 Methods

A building spatial design is defined in this work as a collection of spaces that is arranged in an orthogonal grid. Note that this restricts non-orthogonal shapes and orientations of spaces (for simplicity).

A building spatial design can be represented by either the Movable and Sizable (MS) representation or the SuperCube (SC) representation, see also Figure 1. The SC-representation defines a building by a sizable 3D-grid of cells. A binary variable for each cell and each space then determines whether a cell describes a part of a space. The SC-representation has been developed for use with an optimization algorithm. The MS-representation defines each space by a location and dimensions, and has been developed for use in design processes simulations.

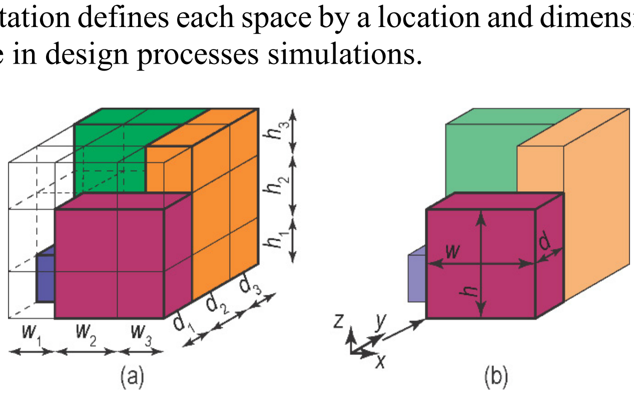

Figure 1: Building spatial design representations. (a) SuperCube (SC). (b) Movable and Sizable (MS).

A building spatial design can be evaluated for: (i) strain energy, which is the internal energy of structural components due to a displacement, and (ii) thermal heating and cooling energy, which is the energy that is required to keep the temperature of spaces within a comfortable range. To evaluate a building spatial design, the so-called design grammars are employed, which are sets of design rules that generate design information based on part of a building spatial design. Two design grammars are used, one to generate a structural finite element model to compute strain energies, and another to generate a thermal resistor-capacitor network to compute the heating and cooling energies. For a more detailed description of the representations and the design grammars the reader is referred to [5], and for the used settings and the subsequent evaluations to [6].

Three methods have been developed: Method (I) uses an Evolutionary Algorithm (EA), i.e. the tailored SMS-EMOA as presented in [7]. Method (II), simulations of co-evolutionary design processes (SCDP), simulates a design process by removing and adding spaces. Two different selection approaches for removal of spaces are used, one uses k-means clustering to cluster spaces based on their performance, the other groups the spaces at the boundaries of a building spatial design and removes one such grouping based on the collective performance. New spaces are added, by splitting the largest spaces in two new ones. For more details, the interested reader is referred to [6]. Finally, method (III), a hybrid method, uses both methods (I) and (II) in a sequential manner following a so-called high-level hybridization scheme [8].

3 Results

The three methods (I-III) have been employed for a building spatial design of 50 spaces and a floor surface area of 750 m^2. For detailed information on the settings of the methods, the reader is referred to [6].

Figure 2 shows the results of the EA applied to a supercube of 6×6×6 cells. Each dot in the figure represents the performance of a solution and the gradient represents the birth time. The EA has been run 10 times to avoid a sensitivity to the stochastic initialization, and the results over all 10 runs are plotted in Figure 2. Additionally, the Pareto Front Approximations (PFAs) after 500 and 5000 EA-evaluations (per run) are plotted, where a PFA consists of the performances of all non-dominated solutions. A solution is dominated by another solution if that other solution performs better or the same in all objectives and better in at least one objective. On the right of the figure, the best structural, the best thermal, and the knee-point designs are visualized for both PFAs, where the knee-point design is a solution that compromises between the objectives.

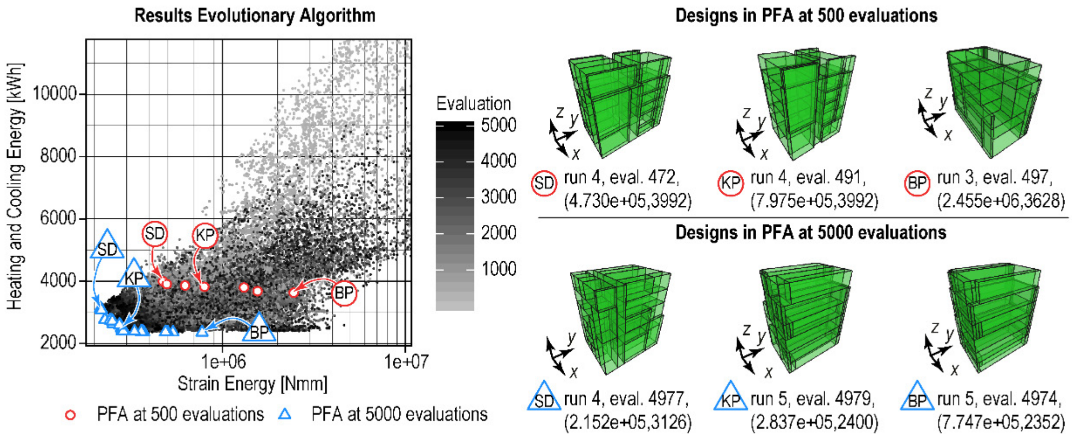

Figure 2: Results of the EA, as presented in [6].

The results of both SCDP approaches on the design problem are shown in Figure 3, on the left. Each plot shows the design path of three SCDP runs: evaluating only structural performance, evaluating only thermal performance, and evaluating both objectives simultaneously. Here, a design path is the set of solutions that were found during a single SCDP run in the order that they were found. Moreover, the design path that has led to the knee-point design is visualized on the right of Figure 3.

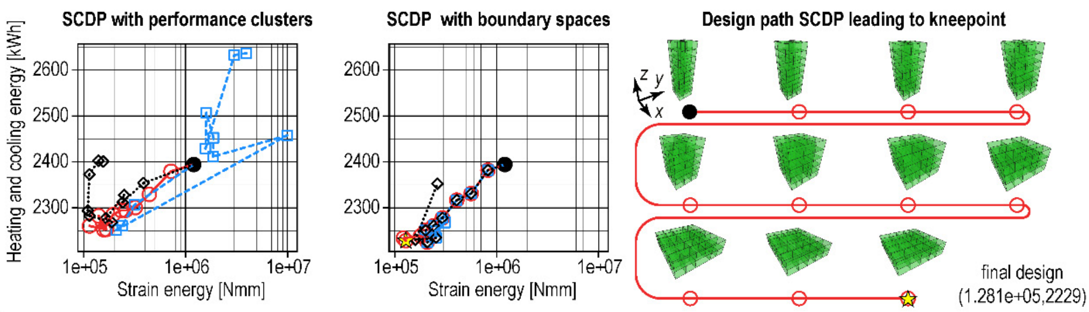

Figure 3: Results of SCDP, as presented in [6].

Finally, the result of the hybrid method is given in Figure 4. The hybrid method first employs the EA for ten runs (to reduce sensitivity to initialization); each run for 500 evaluations. Thereafter, SCDP is applied to the best structural, best thermal, and knee-point solutions that were found by the EA, which are in total 198 evaluations. The knee-point design that is found by SCDP is subsequently used to define a new supercube, after which a new iteration of the hybrid method can be started. In a final iteration, the EA is employed for 3604 evaluations per run.

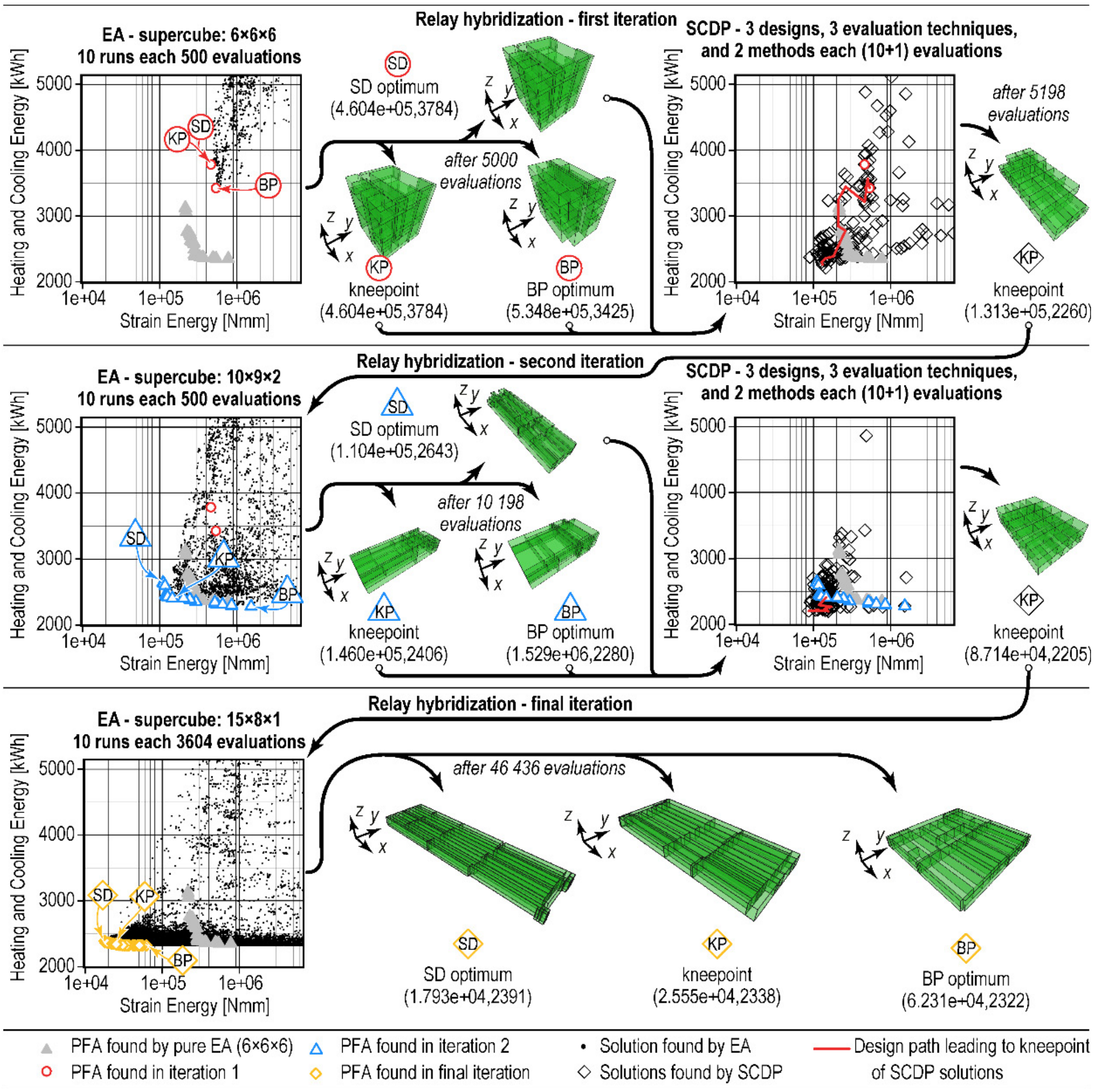

Figure 4: Results of the hybrid method, as presented in [6].

4 Conclusions and Contributions

From a comparison between the EA and SCDP (Figures 2 and 3) it can be observed that, unlike SCDP, the EA is able to find well distributed PFAs. This is useful because such fronts can be used to learn about the characteristics of optimal solutions. Moreover, when looking at the required number of evaluations, it can be observed that SCDP uses less evaluations than the EA while reaching better results. This can be attributed to the ability of the EA to explore the supercube: (1) The supercube may exclude certain designs. (2) Due to the many binary variables of the supercube, many discrete subspaces exist in the design search space, which makes it difficult to be explored by the EA.

The hybridization of the EA and SCDP has been carried out to combine the benefits of each method, while diminishing their disadvantages. In Figure 4 it can be observed that the hybrid method can find a well distributed PFA through the employment of the EA. On the other hand, thanks to SCDP, the hybrid method finds solutions that perform similar (in the second iteration) to the solutions found by the EA alone (in Figure 2), while using less evaluations. Also, with a similar evaluation budget, the hybrid method can find better solutions compared to the case in which only the EA is employed. The hybrid method also succeeded in redefining the supercube such that the EA was able to find better solutions. As such the use of the co-evolutionary principle has proven to be useful, i.e. the interaction between the solution and problem spaces, which is also observed in the design processes of designers [3].

This study concerned a real-world design problem that can benefit from optimization, but which may be difficult to approach using state-of-the-art optimization algorithms. The study showed for the design and optimization of a building spatial design that knowledge observed from design practice can improve the application of an optimization algorithm. Future work will focus on the design and optimization of non-orthogonal building spatial designs. Another direction for future development lies in the integration of the presented methods into the design process of designers. This is envisioned as a design support method in which designers are interactively offered suggestions, which are defined using the design decisions of the designer together with the optimization results.

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