CO-EVOLUTIONARY DESIGN PROCESSES APPLIED TO BUILDING SPATIAL DESIGN OPTIMIZATION

Sjonnie Boonstra[1*], Koen van der Blom[2], Hèrm Hofmeyer[1], Michael T. M. Emmerich[2]
[1]Department of the Built Environment, Eindhoven University of Technology, Eindhoven, Netherlands
Corresponding author: s. boonstra@tue. nl
[2]Leiden Institute of Advanced Computer Science, Leiden University, Leiden, Netherlands

Abstract

Building spatial design is in practice a co-evolutionary design process. To optimize a building spatial design, an evolutionary algorithm can be used, but the search space is large and complex. In simulations of co-evolutionary design processes, the size and complexity are not hindering the search. Such simulations are in the presented work proposed for finding search spaces that are small but still contain high quality solutions.

Key words: Building Design, Co-evolutionary Process, Evolutionary Algorithm, Structural Design, Thermal Design

1. Introduction

Building Spatial Design (BSD) entails the search for the spatial layout and the dimensions of a building for a given set of design requirements. In design practice, it is traditionally performed as a co-evolutionary design process. Here, co-evolution is the principle in which not only the design solution can change, but also the design requirements, and typically the solution and its requirements interact [1]. For example, for a building spatial design a structural design is generated such that a structural performance can be computed. If, in the structural model of this example, components are modified, removed, or added in order to improve the structural performance (e. g. by topology optimization), it is possible that a space in the building spatial design cannot exist or must be modified before it can accommodate the changes made to the structural design. Changing the BSD, consequently changes the design requirements with which the structural design was generated. Building spatial design can also be formulated as an optimization problem, although the search space that contains all possible solutions is large and complex. Modern optimization techniques can search for building spatial designs only in a search space which size has been reduced, which is typically achieved with a so-called super structure. A super structure is a representation of the design problem in which design variables are fixed or limited to a certain range [2]. Unfortunately, a super structure may exclude Pareto optimal points. In earlier work a super structure free optimization technique named simulation of co-evolutionary design processes (SCDP) together with a super structured evolutionary algorithm (EA) has been applied to building spatial design optimization [3]. The work suggested that SCDP may be able to find better solutions than the EA (this was also observed in [4]), albeit that they lie outside of the super structure of the EA. It was also observed that in the same search space the EA is better than SCDP in finding high quality solutions.

In this work, the ability of SCDP to improve a design is investigated. Additionally, it is studied whether the search direction of SCDP can be controlled. If so, it would be possible to find a super structure for an EA that is suitable for specific objectives. The studies performed in this work will be in the scope of structural building design and thermal building design. Therefore, two objectives are defined: minimizing the strain energy; and, minimizing the sum of the heating and cooling loads in the building. A parameter study is employed for the investigation into SCDP, which is introduced in section 2, together with the problem representations, objective evaluations, and the SCDP and EA algorithms. The results are then presented in section 3, and finally, in section 4 the conclusion and outlook are given.

2. Methodology

The methodology of the presented work is presented as follows. First, the used problem representations for a building spatial design are given. Thereafter, the evaluation of the optimization objectives is explained. Accordingly, two optimization methods are introduced, an evolutionary algorithm and SCDP. Finally, the setup of a parameter study is presented which will give insights into the ability of SCDP to improve designs and steer the search.

2.1 Building Spatial Design Representations

Two building spatial design representations have been developed within the research framework of which this work is a part. Both representations are limited in the sense that they can only represent cuboid spaces that are arranged in an orthogonal grid. This limitation is adopted to simplify various optimization phenomena like mutation/modification and constraints. As such, research (like the work presented here) need not be distracted by special cases introduced by e.g. round spaces. The first representation to mention is the so-called "SuperCube" (SC) representation, which is a collection of cells that is defined by a 3D grid. The grid can be dimensioned for each column/row in each direction individually. Each space is then defined by a different bitmask, with which each cell is activated or de-activated for that space. This representation has a fixed number of variables, making it well suited to traditional EA's. The second representation is the so-called "Movable and Sizable" (MS) representation, which is a collection of spaces. Each space in the MS representation is defined by two vectors, location and (orthogonal) dimensions. A spatial design in MS representation can—in contrast to the SC representation—be easily imagined by the human mind. This is useful for SCDP, in which modification steps are defined using the intuition and experience of an engineer. For the interested reader, a detailed description and visuals of both representations can be found in [5].

2.2 Optimization Objectives

Two optimization objectives are defined, minimal strain energy for Structural Design (SD) and the minimal sum of heating and cooling loads for building physics (BP). These objectives cannot directly be obtained from a BSD itself. Therefore, so-called design grammars are used to generate the structural and the building physics model, these are detailed below.

The structural design grammar places a flat shell component that represents a concrete structure ($E = 3.00e4$ N/mm^2; $t = 150$ mm; $\nu = 0.3$) at the location of each wall and floor in the building spatial designs. Wind loads (pressure: 1.0 kN/m^2; suction 0.8 kN/m^2; and shear 0.4 kN/m^2) are placed on the external flat shells, four wind load cases are defined, one for each azimuthal direction ($+x, +y, -x, -y$). Moreover, a life load (5.0 kN/m^2 in $-z$-direction) load case is added to the model on each floor in the structural model. Constraints in x—, y—, and z-direction are placed on horizontally oriented edges that have a z-coordinate at or below zero ($z \leqslant 0$). Each flat shell component is meshed into 3 by 3 quadrilateral elements describing normal—, shear—, and bending action using 2×2 integration points (Gaussian quadrature). After meshing, the resulting system is solved by using direct sparse LLT Cholesky factorizations. The SD objective is then calculated by taking the total sum of strain energy (Nmm) over all elements in the structural model. For a space's performance, the strain energy of all elements that border a space is summed, note that in this way one element can be considered for one or two spaces simultaneously.

The building physics design grammar places a construction at the location of each wall and floor in the building spatial model. Each construction has a thickness of $t = 150$ mm, a specific weight of $\gamma = 2400$ kg/m^3, a specific heat capacity of $C = 850$ J/(K·kg), and a thermal conduction coefficient of $\lambda = 1.8$ W/(K·m), which represents the thermal behavior of concrete. Additionally, an insulation layer is added on the exterior of the external walls and floors ($t = 150$ mm; $\gamma = 60$ kg/m^3; $C = 850$ J/(K·kg); $\lambda = 0.04$ W/(K·m)). The BP model is a Resistor Capacitor (RC) network, in which, constructions and spaces are each modelled by one temperature point. The heat capacity of a construction or space is modelled by a grounded capacitor. Connections between spaces and constructions are modelled with a resistance. At each space's temperature point, an ideal power source is modelled with a capacity of 100 W/m^3 for both cooling and heating. If the temperature of a space rises above a setpoint of 25℃, cooling is activated, if it drops below a setpoint of 20℃, heating is activated. The outdoor temperature in the model is modelled with real world measurements obtained at De Bilt in The Netherlands [6], and for the ground temperature a constant temperature of 10℃ is modelled. Two periods of each 3 days (72 hours) are simulated, a typical warm period (July 2nd-4th 1976) and a typical cold period (December 30th 1978-January 1st 1979). A warm up period of four days is prepended to both simulation periods in order to start the periods with appropriate initial temperatures. The RC-network is described by a system of ordinary differential equations, which is solved by the 5th order Dormand-Prince algorithm using error control. The BP objective for each space is then calculated as the sum of heating and cooling power over the simulated periods. The objective value for the entire building is calculated as the sum of the objective value per space over all spaces. A more detailed explanation of the design grammars and the evaluation of objectives can be found in [5].

2.3 Evolutionary Algorithm

In this work the tailored SMS-EMOA algorithm published in [7] is used for multi-objective optimization. The algorithm uses the SMS-EMOA algorithm with tailored mutation an initialization operators, such that these do not generate infeasible designs. For constraints, specific parameter configurations, and other details the reader is referred to [7].

2.4 Simulation of Co-evolutionary Design Processes (SCDP)

An algorithm that is designed to simulate a co—evolutionary design processes are introduced next. In principle, the algorithm removes a number of spaces, and splits an equal amount of the remaining spaces. For this, it looks at the objective values per space and it takes two arguments: a space removal ratio, here denoted by η_r ; and a sorting method, denoted by η_s .

The sorting parameter η_s specifies how a certain objective is sorted, and which objectives are considered in the sorting process. An objective is included in the sorting process if it is supplied with two two—letter terms, of which the first term specifies the objective itself ("*sd*" or "*bp*") and the last the ordering. For the sorting process, the objective values are normalized between 0 and 1 in two different ways: "*lh*", the minimum is normalized to 0 and the maximum is normalized to 1; or vice versa "hl", maximum to 0 and minimum to 1. If both objectives are accounted for the parameter is a concatenation of two pairs of terms, where each pair is concatenated with a "+". For example $\eta_s =$ "*sdlh*+*bplh*" denotes that both SD and BP objectives are included, and their respective minima are normalized to 0 and their maxima to 1. Once the normalized values are computed, two sorted lists are computed: the "best" list contains—per space—the Euclid distance from a vector containing the normalized objective value to the utopian point; and the "*worst*" list is similar, but contains distances in reference to the dystopian point. Here the utopian point is the $\vec{0}$ vector and the dystopian point is the $\vec{1}$ vector, where each vector's dimension equals the number of considered objective values.

Space removal is based upon a selection from the "*worst*" list, where the number of removed spaces is n_{del} and the removed spaces are the n_{del} spaces with the lowest values in the list. Here, n_{del} is set to n_{low} if $n_{\mathrm{up}}/n_{\mathrm{tot}} > 0.5$ and is set to n_{up} otherwise, where n_{low} is a lower bound of spaces to be removed, n_{up} an upper bound, and n_{tot} the total amount of spaces in the BSD. The values for n_{low} and n_{up} are determined via a bi-sectioning algorithm that finds a value a and a value b within a margin of 0.01 where $a < b$. Accordingly, the bounds are determined as follows: n_{low} is the number of values in the "*worst*" list that is less or equal to a , and n_{up} is the number of values in that list that are lower or equal to b . In each iteration of the bi-sectioning algorithm $(a+b)/2$ is assigned to a if the number of values in the "*worst*" list that is lower than that value is less than $\eta_{\mathrm{ratio}} \cdot n_{\mathrm{tot}}$, otherwise it is assigned to b .

After n_{del} spaces are removed, the remaining spaces are scaled in x— and y— direction by a factor of $\sqrt{V/V_0}$ in order to restore the BSD's volume V to the original volume V_0 . After scaling, n_{del} of the remaining spaces are split, starting at the top of the sorted "best" list. When split, a space is divided in two halves along the direction of its smallest horizontal dimension, if the two horizontal dimensions are within 1% of each other, the space is split along the x-direction. If splitting a space would lead to a dimension smaller than 500 mm, the space is skipped, unless there are not enough spaces left to reach the criteria of n_{del} split spaces. The latter prevents spaces from becoming too narrow, and also enforces one of the constraints that is imposed on the BSD for the EA optimization (see [7]).

2.5 Parameter Study

In order to assess the ability of SCDP to improve the results of optimization with EA, first the EA is employed for an optimization task. The supercube for that task is set to contain a grid of $3 \times 3 \times 3$ cells (x , y , z), with which 10 spaces should be defined. A volume constraint for the total building volume is set to 357 m^3. The EA's evaluation budget is set to 1e+4 of which the first 50 are the initial population. To avoid a large dependency on the stochastic initialization and variation the EA is run 35 times using these settings. The results from all 35 runs are depicted in Figure 1, a grey/black dot represents the performance of one evaluated design, the gradient represents at which iteration the performance was found. Note that the axis on which the strain energy is plotted uses a logarithmic scale. The Pareto Front Approximation (PFA), is here the set of non-dominated points. Depicted with blue triangles is the PFA over all runs after all iterations, depicted with red circles is the PFA over all runs after just 100 iterations. Note that, in order to take into account stochasticity, the median of all PFAs over all runs would be representative. However, here the best solutions overall are chosen so that SCDP can be compared with the best found designs in the chosen supercube.

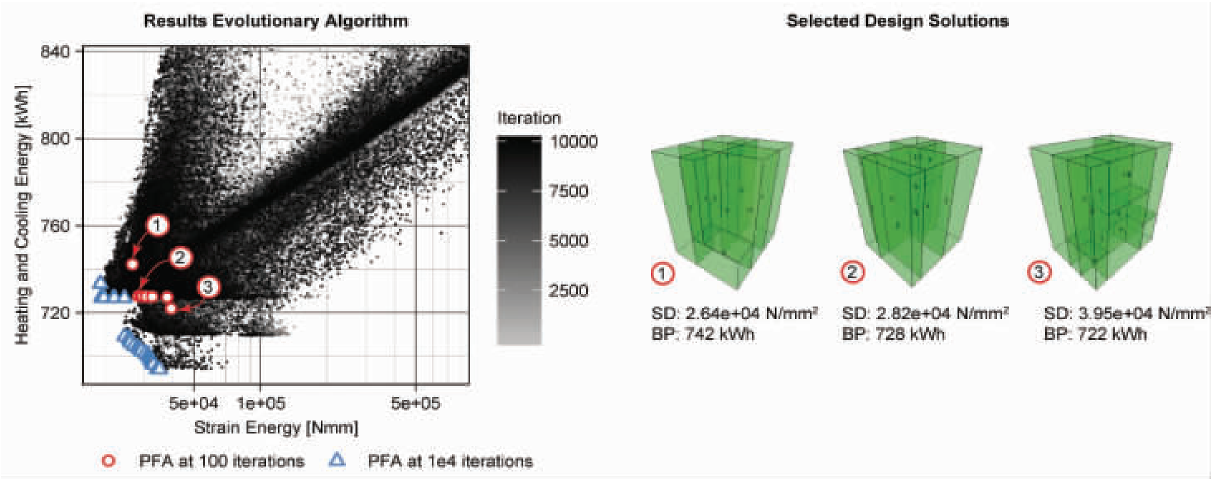

Figure 1. Results from the evolutionary algorithm and a visualization of the selection of building spatial designs

For the parameter study, three designs are selected from the EA's results, which are depicted on the right in Figure 1. These designs serve as initialling BSD's onto which the SCDP algorithm will be applied. In the parameter study, the sorting parameter η_s will be varied in every unique mutation of its terms, which yields 8 configurations for this parameter. Furthermore, the space removal ratio η_r , will be varied with the following values {0.1, 0.2, 0.3, 0.4, 0.5}. As such, the increment of 0.1 for the η_r parameter signifies one space for a BSD with 10 spaces and thus 1, 2, 3, 4, or 5 spaces can be removed. Finally, SCDP will be applied successively as well, i. e. search depth, for this parameter study SCDP will be applied successively for four iterations. This successive application yields a tree structure in the parameter study for both η_r and η_s , however only η_s will be varied after each successive SCDP application. Altogether, $3 \cdot 5 \cdot 8^4 = 61440$ configurations can be evaluated with $3 \cdot 5 \cdot \sum_{i=0}^{3} 8^i = 8775$ evaluations if each node in the search tree is evaluated once.

3. Results

The results of the parameter study are shown in Figure 2, each evaluated design's performance is indicated with a grey dot, the PFA from the EA with a blue triangle, and the selected designs (1, 2, and 3) with a red circle. The PFA of the SCDP results is depicted with a green rhombus, a selection of these is shown on the bottom right. The SCDP results are plotted in three folds, in each plot the convex hull of a distinct collection of performances is drawn. At the top left of Figure 2, a distinction is made in the initial design that was selected from the EA results. From this plot, no clear distinction can be observed with respect to the initial design, which suggests SCDP is not significantly sensitive to the initial design. When a distinction is made in the space removal ratio η_r (top right), it seems that higher ratios lead to better designs, and a ratio of 0.1 does not seem to improve at all. Finally, a distinction in the search depth shows that just two iterations of SCPD in the parameter study barely lead to better results. However, in the third and fourth iterations improvements are found. From the plots it can be concluded that it is beneficial to have at least 3 successive SCDP steps with a relatively high space removal ratio (0.4-0.5).

When looking at the supercube of the designs in the bottom right of Figure 2, it can be concluded that by using SCDP different supercube sizes have successfully been found. The newly found supercubes are lower but wider, which allows all spaces to be placed on the ground floor. This is beneficial for the structural design objective as the wind and life loads can be transferred to the boundary conditions in a more direct path, therefore generating less strain energy. Also note that the sizes of the supercube in Figure 2 (12 and 16 cells) are smaller than the size of the supercube used for the EA (27 cells), thus the search spaces of the found supercubes are smaller whilst they contain better solutions.

Although the performances of the designs improve after using SCDP, it should also be noted that only the structural design objective seems to benefit from applying SCDP. This can be explained from the fact that a perfect cube is in this case optimal for thermal building design because it has the smallest possible surface to volume ratio in the orthogonal case. From the EA results, it can be seen that the EA can already find such optimal designs.

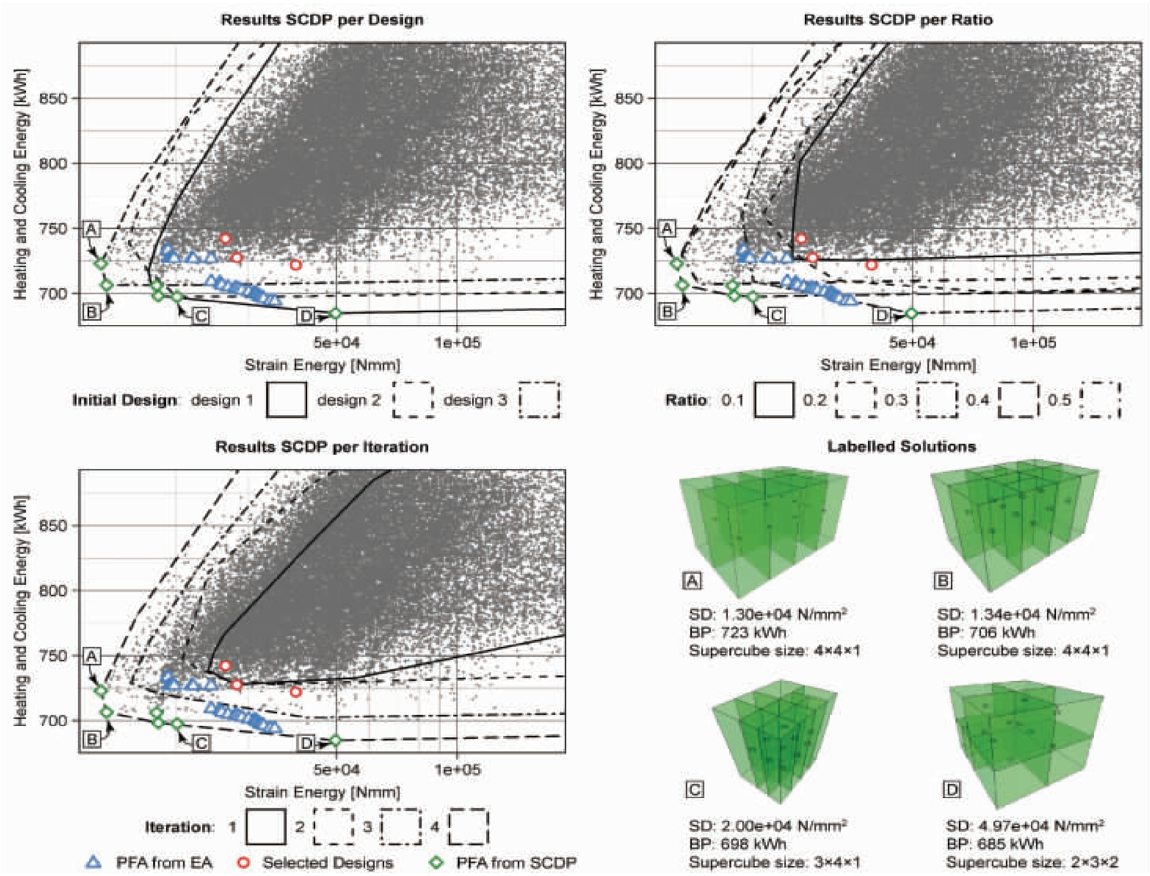

Figure 2. Results of SCDP with convex hull of performances per design (tl), space removal ratio (tr), and iteration (bl).

It may be clear that SCDP is able to improve the results found by an EA, albeit in a different search space. However, for the sake of supporting an EA by finding suitable search spaces, it is of interest to steer the performance of a design into certain directions. As stated, SCDP does not seem to be able to improve the BP objective in the parameter study, but it would be interesting to see if the improvements in the SD objective can be generalized into a set of SCDP steps that guarantee an improvement. Unfortunately such a clear conclusion cannot be drawn from the presented work. Even though some sorting configurations for η_s seem to be more likely to improve a BSD, when looking at the sorting steps made for each SCDP in Figure 3 no clear preference or pattern can be observed. Additionally, the depicted design paths also contain values for η_s that—judging from the statistics of the parameter study—seem highly unlikely to improve a design. In Figure 3 it can be observed that every design path first leads to worse designs before it leads to a better design. This makes it more difficult to generalize the configurations for the sorting parameter η_s.

3.1 Discussion

The presented work has showed that SCDP is able to improve designs, and as such it can be used to find suitable search spaces for optimization with an EA. However some critical remarks should be made. First, the implemented SCDP modification is naïve as it is not reasoning from a physics point of view, but merely from an objective value point of view. A better modification for SD might be—for example—to split a space below a floor with high strain and to remove a wall with low normal forces. Second, no clear answer was found on the question if SCDP can steer a BSD's performance into a certain direction. Additional studies that aim to find such SCDP configurations should be performed to conclude on that.

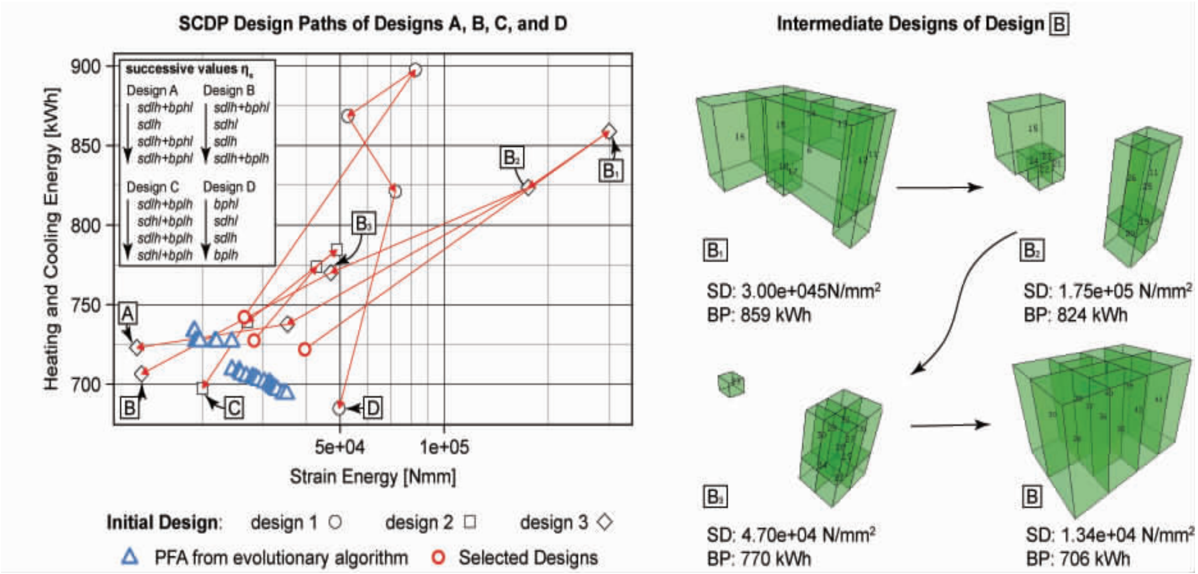

Figure 3. Design paths of designs A, B, C, and D, which are obtained from the SCDP PFA (see also Figure 2).

4. Conclusion and Outlook

In this paper, an algorithm that simulates a co-evolutionary design process (SCDP) of building spatial designs is introduced. It is reasoned that SCDP can help optimize using evolutionary algorithms (EA), by finding promising search spaces. A parameter study is performed on the SCDP algorithm, using designs that were found by the EA. It has been shown that better designs than the EA's results can be found using SCDP, albeit that they lie in a different search space. The latter proves that SCDP can be used to suggest suitable search spaces to EAs. However, the parameter study did not prove to be sufficient in identifying the parameters that allow to steering the performance of a building spatial design into specific directions. Therefore, future work will focus on further development and research of the SCDP algorithm in order to be capable of steering a design's performance into specific directions.

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