# Combined Super-Structured and Super-Structure Free Optimisation of Building Spatial Designs

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**Abstract.** This paper proposes a new method for multi-disciplinary optimisation of building spatial designs in the preliminary design stage. First it discusses two recently developed building spatial design optimisation methods, one using a super-structured approach and the other applying a super-structure free approach. Subsequently, a combination of the two methods into a new hybrid method is presented. A case study is demonstrated to compare the three methods based on their performance and the characteristics of their design evolution. First results show that the hybrid method could aid in the effective exploration of large design search spaces by selecting more confined design search spaces based on engineering knowledge.

## 1. Introduction

The process of building design optimisation is still strongly dependent on input from numerous engineers and designers, simply because the design search space is too large to be overseen by any single stakeholder. This limitation motivates computer scientists to constantly develop new techniques that try to find the global optimum by considering as many solutions as possible without bias. Taking into account every possible solution is, however, computationally infeasible. This paper proposes a new method that uses engineering knowledge to steer the process into interesting sub-domains of the design search space to increase the efficiency of and limit the strain on optimisation algorithms.

One domain in the research on optimisation focuses on multi-objective optimisation by use of evolutionary algorithms, which find a subset of designs to approximate the Pareto optimal front in a predefined search space. Here, a Pareto optimal front is a set of solutions that are characterized by being non-dominated, i.e. no other solutions are defined that perform better for any objective without there being a decrease of performance for any of the other objectives first. State-of-the-art optimisation algorithms such as NSGA-II (Deb *et al*, 2002) or SMS-EMOA (Beume *et al*, 2007) use random selection of solutions and random mutation or crossover on previously found solutions to find the Pareto front. The Hypervolume-based Subset Selection Problem (HSSP), as presented by Kuhn *et al* (2016) and Bringmann *et al* (2014) focuses on the selection of the solutions: If the found Pareto Front Approximation (PFA) contains more points than desired, a reduction should take place; if—on the other hand—fewer points than desired are found, all non-dominated and a diverse selection of dominated points can be selected to reach the desired number.

A drawback of evolutionary algorithms is that they are computationally costly when a rigorous search of large search spaces is attempted. So-called heuristic methods do not have this drawback, as they use a directed and thus fast way to obtain improved designs from the design search space. Heuristic methods are, however, prone to finish the search process when they find a local optimum, rather than the global optimum. An example of a heuristic method is the simulation of Co-evolutionary Design (CD) processes. This method tries to simulate evolutionary processes that are seen in nature where two species interact in a manner where they depend on each other in their evolution. Maher & Tang (2003) present a general method for co-evolutionary design optimisation. Hofmeyer and Davila Delgado (2015) use the principle of CD for building design. They base a simulation of a co-evolutionary design process on the interaction that building design engineers have during the design of buildings. A relatively new development concerns meta-heuristic algorithms, which improve the performance of evolutionary algorithms by adding heuristic methods to the search using hybridisation (Talbi, 2002). Hybridisation is defined here as a combination of two or more methods that share a common goal, such that the hybrid method inherits the positive features of each method.

As mentioned, evolutionary algorithms use a predefined search space, which is often referred to as a super-structure. Thus, a super-structured optimisation method operates on a predefined design search space, meaning that the set of solutions in this search space is limited to a finite number. On the other hand, for a super-structure free optimisation method no limit is placed on the design search space, and parts of a design can be freely modified, added, or removed. Most optimisation methods cannot handle super-structure free optimisation, since they assume a fixed number and type of parameters. Voll *et al* (2012) show that it can be beneficial to consider a super-structure free method to find new and possibly unexpected solutions that would otherwise not be found because they were not included in the super-structure. Kim and Kwak, (2002) automatically adapt a super-structure over time, such that the design space is either refined, extended or reduced, based on previous optimisation results.

The need for the reduction of building footprints, both environmentally as well as financially, has driven extensive research on the optimisation of building designs. Díaz *et al* (2017) review Multi-Disciplinary Optimisation (MDO) in the built environment and present practical problems to be solved in future research. Geyer (2009) presents work on the implementation of optimisation methods in Building Information Modelling (BIM) that also take user interaction into account. User interaction is considered by Steiner *et al* (2016) too, who present an algorithm that generates structural layouts based on spatial designs produced by architects. Many papers present an implementation of existing optimisation methods in Computer Aided Design (CAD) or BIM design frameworks. For example, Rahmani Asl *et al* (2015) and Welle *et al* (2011) both present building thermal design optimisation in a BIM-based design search space. Caldas (2008) show the capabilities of an optimisation oriented CAD environment in which user defined design variables may be optimised by an evolutionary algorithm. A limited amount of work also focuses on considerations for tuning and the development of building specific optimisation methods. For instance Mora *et al* (2011) propose a method to provide designers with feedback on the life-cycle costs during the design process. Gero *et al* (1983) demonstrate a model to represent and compare design alternatives in order to asses an objective in a context with other objectives. Hamdy *et al* (2016) present a comparison between several tuned optimisation methods to study the efficiency and the performance of different algorithms. Finally, Hopfe *et al* (2012) propose a method to predict the impact of design variables on the design's optimality.

As indicated above, for building design optimisation, the distinction between super-structured and super-structure free methods has not been taken into account explicitly so far. Also, an MDO method for preliminary building spatial designs does not exist. And finally, no hybridisation between knowledge-based building design optimisation and state-of-the-art evolutionary algorithms has been developed. For this reason, Boonstra *et al* (2016) defined the basis required for the cooperation between super-structured and super-structure free optimisation for building spatial design. Included were two design representations for building spatial design optimisation: First, a so-called supercube, which was suitable for mathematical programming methods because of its parametric design space. The second being a so-called movable sizable representation that is intuitive for engineers, and applicable for rule based super-structure free optimisation. As a next step, this paper proposes a method to combine the best characteristics of the above methods.

Section 2 elaborates on the two previously developed optimisation methods and their combination into a new hybrid method. An academic case study to compare and demonstrate the existing and new methods is presented in section 3. This is then followed by the conclusions and an outlook in section 4.

## 2. Optimisation Methods

This section presents the developed super-structured and super-structure free optimisation methods. For this the two design search space representations are briefly discussed (Boonstra *et al*, 2016): SuperCube (SC, figure 1a), and Movable Sizable (MS, figure 1b). The supercube has sizable divisions that divide it into cells that can each be activated for a space within the design. The movable sizable representation defines a design by given spaces that are each defined with a location and dimensions. The workings of the super-structured and super-structure free optimisation methods are presented first. This is followed by a description of the new combined method.

### 2.1 Super-Structured Optimisation

The SuperCube (SC) representation has first been applied in building spatial design optimisation by Van der Blom *et al* (2016a). In this paper a canonical evolution strategy was used for single objective optimisation. Moreover, penalty functions were used to navigate away from infeasible solutions. This was followed by Van der Blom *et al* (2016b), where two state-of-the-art evolutionary multi-objective optimisation algorithms have been used, namely the Non-dominated Sorting Genetic Algorithm (NSGA-II, Deb *et al* 2002) and the S-Metric Selection Evolutionary Multi-objective Optimisation Algorithm (SMS-EMOA, Beume *et al* 2007). Van der Blom *et al* (2016b) also tailored the SMS-EMOA algorithm—specifically for the building spatial design optimisation problem—by introducing smart mutation and smart initialisation operators. By taking into account constraints these operators avoid infeasible designs entirely. The design search space is defined by the input for this method: the supercube size, the number of spaces and the total building volume. A comparison between the three techniques has indicated that the tailored version of SMS-EMOA found the most accurate Pareto front approximation, measured by the so-called hypervolume indicator. More recently, Van der Blom *et al* (2017) propose improved initialisation and mutation operators to eliminate bias. Additionally, parameter tuning algorithms have been utilised to find an improved set of parameters for the tailored version of SMS-EMOA. This method has proven to be successful in the optimisation of building designs, but has not yet been tested on larger problem sizes (i.e. supercube size and number of spaces) that are needed for larger buildings.

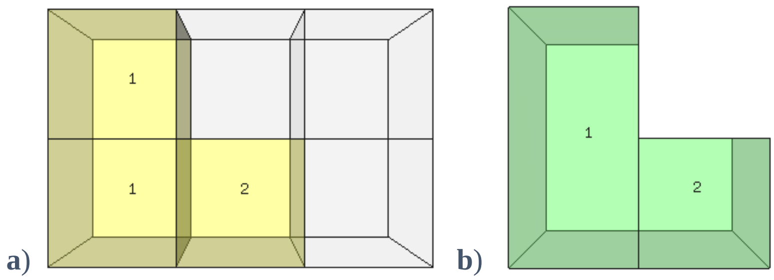


Figure 1: a) SC-representation, "active" cells (here yellow) describe a space within the supercube. b) MS-representation, each space is defined by its location and dimensions

### 2.2 Super-Structure Free Optimisation

Using the Movable Sizable (MS) representation, at Eindhoven University of Technology Hofmeyer & Davila Delgado (2015) performed simulations of Co-evolutionary Design (CD) as proposed by, among others, Maher & Tang (2003) to find structurally optimal building spatial designs. As part of these simulations, worst performing spaces were deleted from a given design, and some remaining spaces were split and the design was scaled to restore the number of spaces and volume of the initial design. Current research in Eindhoven focuses on finding a general approach of CD for multi-disciplinary optimisation of building spatial designs. This requires a technique to select a number of variables (which here are spaces) that should be removed or modified, for example by clustering the performance data of a design. Moreover, different modification techniques have to be developed that can modify designs to perform better for at least a single objective. Diversity in these modification techniques is desired as, firstly, it increases the chance that a solution can be steered towards Pareto optimality, and secondly it gives the possibility to consider more solutions in the design process. This method has proven to find better designs quickly, but it is sensitive to local optima.

### 2.3 Combination

A combination of the previously mentioned methods was proposed to employ the best of both without including their bad characteristics, i.e. employ speed and quality without computational costs. A combination does however also yield new parameters to consider. First of all is the scheme in which the different methods are executed. Useful suggestions for such schemes can be found in the research domain of hybrid metaheuristics, where local and global search methods are combined. Secondly, a selected scheme inevitably involves more new parameters, specific to the selected scheme and the used method. Finally, the information transfer between methods also involves parameters, e.g. which designs are selected for a computationally expensive local search? This subsection presents two (hybridisation) schemes from Talbi (2002) and relevant new parameters.

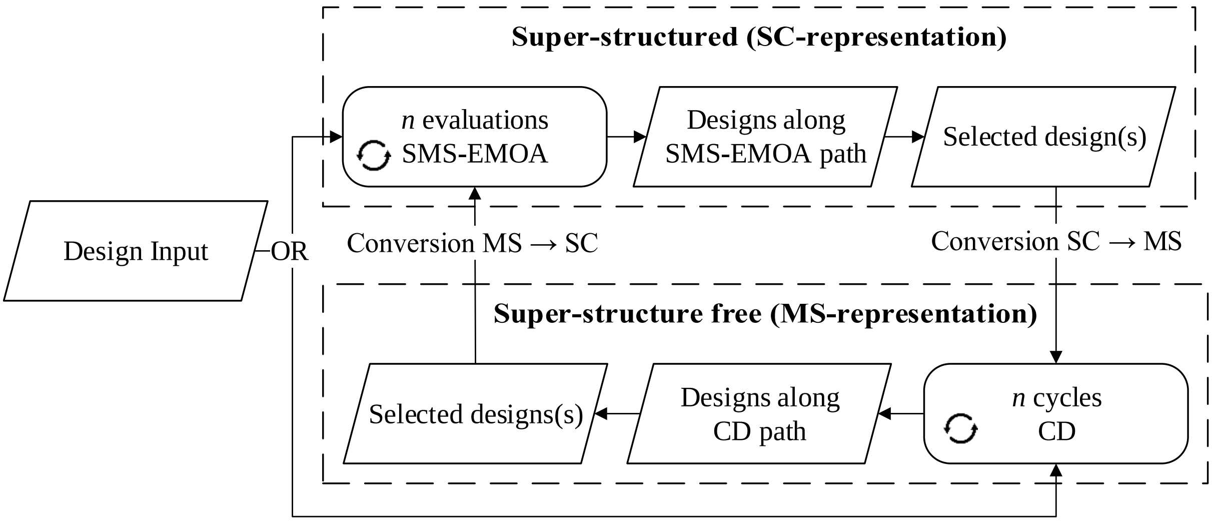


Figure 2: Relay combination of the optimisation methods

*Relay.* A straight forward combination of methods is the relay scheme as shown in figure 2. Methods are executed in relays, and apart from the first, each method is initiated with the results from the previous method. This scheme can be made more competitive by making the transfer to another method conditional: The next method is then conditionally called, depending on the performance of the previous. If the previous method performs satisfactory nothing changes, otherwise another method will be used.

*Teamwork.* The teamwork scheme as shown in figure 3 causes the combined methods to compete. Methods are run in parallel, where after selected solutions are used as starting points for a new parallel session of the methods.

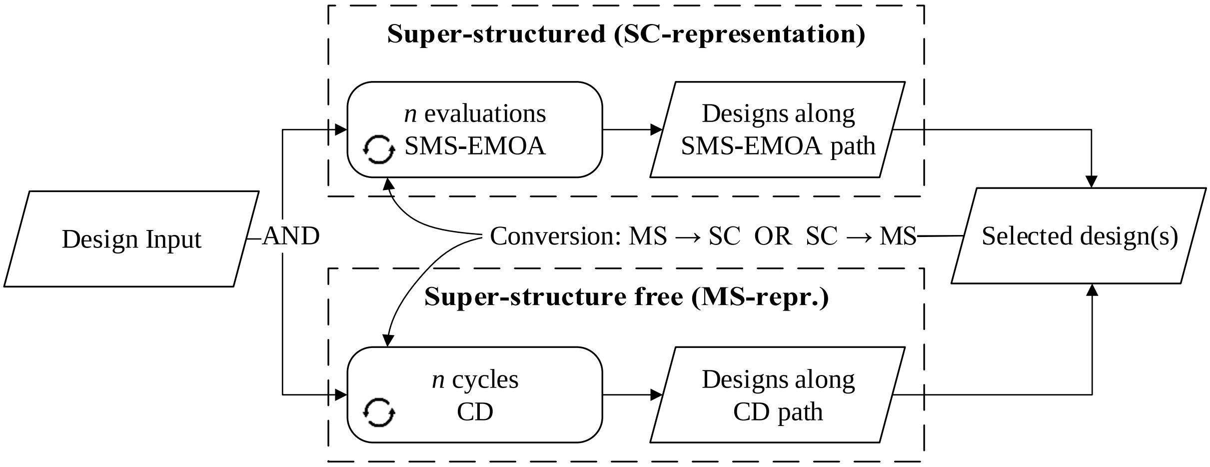


Figure 3: Teamwork combination of the optimisation methods

**Parameters.** A number of parameters has to be considered for the combination of the optimisation methods: with respect to the design selection; the initial method; the depth of search for each method; and the conversions between the representations.

*Design Selection.* For each iteration, a method generates a number of design solutions, of which one or multiple have to be selected for the next method. Pareto optimality could help in this selection; however, the number of designs that are contained in a Pareto Front Approximation (PFA) varies. Thus, selecting the entire PFA could lead to excessive computational costs, and in the case of SMS-EMOA it could result in an initial population larger than the chosen population size. Therefore, it could be considered to use the single so-called knee point, which is the point that lies closest to the minimum point. Hypervolume-based subset selection (Kuhn *et al*, 2016 and Bringmann *et al*, 2014) selects a representative subset (a specified number of points) from a PFA, and could be another approach to select the design to be continued.

*Initial Method.* The choice for the initial method determines the required design input. Namely the CD method needs an initial design consisting of spaces with their locations and dimensions, whereas SMS-EMOA requires the number of divisions in the supercube, the total building volume, and the number of spaces. Additionally, the choice for a sequence of methods will clearly affect the search path of the combined approach and thus will strongly influence the results.

*Evaluation Budget.* The evaluation budget, or the number of evaluations for each method, is of interest because a-priori it is not known how fast a method will find the optimum. If the budget is too low the method might find sub-optimal solutions, and if the budget is too large computation time is wasted. The optimal budget is problem and method specific and can only be found by tuning algorithms and by experience.

*Conversion.* A transfer between methods involves a conversion of the selected designs to another representation as described by Boonstra *et al* (2016). However, this is not straight-forward for a transfer from the CD method to SMS-EMOA because of the following: The input of SMS-EMOA is a supercube, thus a design is defined by a specific supercube plus a selection of activated cells. As such, either it has to be decided to regard the specific supercube as sufficiently describing the CD design, or to generate the initial individuals not only via the initialisation operators but also by activating cells such that the selected CD design(s) occurs.

Additionally, it should be noted that supercube sizes may differ when multiple designs are selected to initialise SMS-EMOA, which can only handle one supercube size. This can easily be solved by the addition of empty cells to each design's supercube, such that they can all be represented by the same supercube.

## 3. Academic Case Study

This section presents a case study concerning a building of eight spaces with a total volume of 300 m³. It serves as a demonstration and a first comparison of the developed methods. Settings are given for each optimisation method, as well as the results and a discussion.

### 3.1 Settings

**Design Grammars.** A building spatial design cannot be evaluated on discipline specific objectives without the corresponding discipline specific design properties. These design properties will be created by design grammars, which are sets of design rules that operate on the building spatial design. An alternative for grammars could be optimisation methods or computer learning techniques, but for demonstration purposes here grammars are used. Two design grammars are defined, one for structural and one for thermal building design.

*Structural design.* A grammar for structural design adds structural components like columns, beams, or slabs, and also structural loads and constraints to the building spatial design. For this case study, every surface in the building spatial design is structurally interpreted as a concrete slab of 150 mm thick with a Young's modulus $E$ of $30000\ \mathrm{N/mm^2}$ and a Poisson's ratio $\nu$ of 0.3. Each slab is meshed into 100 flat-shell finite elements, i.e. with a division of 10 elements along each side. For the element formulation a combination of the formulations for in-plane-behaviour as presented by Cook (1974) and out-of-plane behaviour by Batoz & Tahar (1982) is used both with $2 \times 2$ numerical integration (Gaussian quadrature). All nodes in the model that have the global minimal $z$-coordinate are constrained for $x$- $y$- and $z$-displacements. A life load case in $-z$ direction with magnitude $5\ \mathrm{kN/m^2}$ is added to each horizontally oriented slab. Finally, four wind load cases are added to all exterior slabs, one in positive $x$, one in positive $y$, one in negative $x$ and one in negative $y$ direction. The magnitudes are determined with respect to the orientation of the slab and the direction of the load case: Three different magnitudes are defined: suction $0.8\ \mathrm{kN/m^2}$, shear $0.4\ \mathrm{kN/m^2}$ and pressure $1.0\ \mathrm{kN/m^2}$. Finite element equations are assembled into a system of equations, which is then solved using an LLT decomposition as found in the Eigen C++ library by Guennebaud & Jacob (2010).

*Thermal Design.* The thermal design consists out of walls, windows (not used here), and thermal loads. In this case study, the grammar will add to each surface of the building spatial design a concrete wall 150 mm thick, with a specific weight $\gamma = 2400\ \mathrm{kg/m^3}$, a specific heat capacity $C = 850\ \mathrm{J/(K \times kg)}$ and a thermal conduction coefficient $\lambda = 1{,}8\ \mathrm{W/(K \times m)}$. Furthermore, to each exterior surface an additional layer of 150 mm of insulation on the outside is added with $\gamma = 60\ \mathrm{kg/m^3}$, $C = 850\ \mathrm{J/(K \times kg)}$, and $\lambda = 0.04\ \mathrm{W/(K \times m)}$. Then a system of ordinary differential equations is developed by an RC-network of heat resistances and capacitances in which each wall and each space is represented by one temperature point—where that of a wall is located in its centre. The building is heated and cooled by means of an ideal power source of $100\ \mathrm{W/m^3}$ in each space, which is cooling when the temperature is higher than 25 °C and heating when it is lower than 20 °C. A ventilation rate of one air change per hour is defined per space. The outside temperature is imported from a real-world data set that is measured in De Bilt in The Netherlands by the Dutch Royal Meteorological Institute (KNMI, 2016) and a constant ground temperature of 10 °C is assumed. The building thermal behaviour is simulated over the period starting on 01/07/2014 01:00 until 31/07/2014 24:00. The simulator divides each hour into four time steps, which are eventually solved by a Runge-Kutta solver (Ahnert *et al*, 2011).

**Objectives.** For structural design (SD) the objective is defined as the sum of strain energy over all elements over all load cases. This is further referred to as structural compliance. The building physics (BP) or more specifically the thermal design objective is given by the sum of heating and cooling energy over the above-mentioned time period.

**Constraints.** The first and most natural constraint is no-overlap, which prevents building spaces to overlap. The next constraint is employed to guarantee correct conversion between the SC and MS representations by ensuring that for each design aspect the design solution conforms to the most demanding representation: This constraint enforces cuboid building spaces and consequentially also their ortho-convexity, which is necessary because the MS-representation can only represent cuboid (3D rectangular) spaces. To follow this constraint, in the supercube it is checked if the bounding box of a space can be formed by the corner supercube cells. If this is the case then it is checked if the space itself is ortho-convex, i.e. every supercube cell in between the corner cells is activated for that space. Finally, also an implementation specific constraint is defined, which prevents overhanging spaces. This constraint is introduced to make for a fast and efficient implementation of the cuboid and ortho-convexity constraints. Exact descriptions of the constraints and their mathematical notation are available in Boonstra *et al* (2016) and Van der Blom *et al* (2016a). Finally, dimensions of divisions in a supercube in SMS-EMOA are constrained to a minimum to prevent zero width divisions, but also to prevent unrealistic designs from being considered. The lower bounds are set to 500 mm for the width ($x$-direction) and depth ($y$-direction) dimensions and 3000 mm for the height ($z$-direction) dimensions in the supercube. The case study may seem simplistic in terms of the above constraints and problem size, however in (Van der Blom *et al*, 2016a) it is shown that these constraints are frequently violated and non-trivial.

The co-evolutionary approach automatically follows most constraints by using modification rules that are designed not to exceed them. However, this does not apply to the above constraints for minimal cell dimensions and no-overhang. For the CD approach, it is thus still required to check constraints and possibly exclude solutions before they would be used as starting point for the SMS-EMOA method, which has still been done manually for this study.

**CD.** A simple selection and modification rule set is used for this case study, thus only a single solution is generated after each co-evolutionary cycle. This selection and modification rule starts by evaluating the performance of each space in the design for each discipline. These performances are then normalised based on the minimum and maximum points. Here the minimum and maximum points are defined respectively as the points containing the lower and upper bound performance values of each discipline. Subsequently the space associated with the worst performance is removed, where the worst performance is measured by the shortest distance with respect to the maximum (anti ideal) point in the Pareto front for both disciplines. For finding the best performing space, a performance ranking is made in relation to the shortest distance to the minimum (ideal) point in the Pareto front. Finally, the best performing space is selected for splitting unless this splitting creates a space with a side smaller than twice the constraint on the supercube's minimal division width. In that case, the next best ranked space is considered for splitting, et cetera. This is carried out to prevent that too many constraint violating designs are generated by the CD method. A space is by default split in a vertical oriented plane (normal in $(x, y)$-direction) along a line parallel to the $x$-axis, or parallel to the $y$-axis when the space's side in $x$-direction is longer than its side in the $y$-direction. A space is never split in a horizontal plane (normal in $z$-direction). After splitting, the complete design is scaled up equally in the $x$- and $y$-directions to match the original design volume. Scaling of the design completes the selection and modification rule set. The case study is started with a design consisting of two spaces in $x$-, one space in $y$- and four spaces in $z$-direction, where each space measures 3500, 3570 and 3000 mm in $x$-, $y$- and $z$-directions respectively. The CD method will be run for 50 cycles in this case study.

**SMS-EMOA.** The tailored version of this method will be run using tuned parameters that were found in Van der Blom *et al* (2017). It should be noted that these tuned parameters were found for a design search space with five spaces and a different thermal performance objective, namely the minimal outside surface area rather than the minimal heating and cooling energy. The population size $\mu$ is set to 6 designs. Two types of mutation are used: binary, which mutates the cells that are assigned to a space; and polynomial, which mutates the continuous dimension variables. As a result of the tuning, the probability for the binary mutation operator is set to 0.4993 and the polynomial mutation operator is applied otherwise. The number of steps to be taken by the mutation operator is determined by a pooling technique, which chooses uniformly at random to do either a local move (one step) or an explorative move (three steps). A mutation probability of 0.4381 is set for each dimensioning variable in the case that polynomial mutation is selected. The volume constraint is maintained by an iterative repair function, in which the design is continuously scaled to the constrained volume and the dimensional values are continuously reset to their constrained values until the volume deviates at most one cubic millimetre. The remaining constraints are maintained by the smart initialisation and mutation operators, see Van der Blom *et al* (2017) for more details. The supercube for the case study is chosen to be three cells in $x$-direction two cells in $y$-direction and five cells in the $z$-direction, the volume constraint is set to 300 m$^3$. A budget of 5000 evaluations has been chosen for SMS-EMOA, for comparison reasons a Pareto front approximation will be made after 1000 evaluations and after 5000 evaluations.

**Combined Method.** Design selection is performed by selecting the knee point from the Pareto front of all found solutions. Selection based on HSSP (Kuhn *et al*, 2016) remains out of scope for simplicity and brevity. The CD method is selected as the initial method as it is believed that CD will suggest a better design search space before a computationally expensive run of SMS-EMOA is carried out. The combined method will iterate five times, with each iteration consisting of a CD run with 10 cycles and an SMS-EMOA run with a 1000 evaluations. The total evaluation budget of one run of the combined method is then 5050, thus creating the possibility to compare performances with the SMS-EMOA run after 5000 evaluations. During the conversion from MS to SC there will be an extra layer of cells added in the $x$-, $y$- and $z$-directions of the supercube, to prevent the supercube from being too restrictive for the SMS-EMOA design operators. SMS-EMOA will be initialised with an empty supercube, hence not with solutions containing a-priori activated cells, as it was found that such solutions are too dominant over randomly initialised designs. This dominance cannot easily be overcome by the current mutation operator in SMS-EMOA.

### 3.2 Results

Results contain outliers, causing graphs to only show a narrow bandwidth for most solutions. Graphs are therefore only visualised over the bandwidth of interest (i.e. the Pareto front approximation). Figure 4 shows the design path of the CD method, large jumps in performances show that the subtle selection and modification rule (i.e. the removal of only a single space) still has an aggressive impact in terms of performance. As a positive consequence, the CD method can rapidly move to other regions (but not necessarily better) in the design search space. For this case study CD can find a better solution after two cycles, but later iterations show worse performance and oscillation around solutions 7 to 10 after cycle 6.

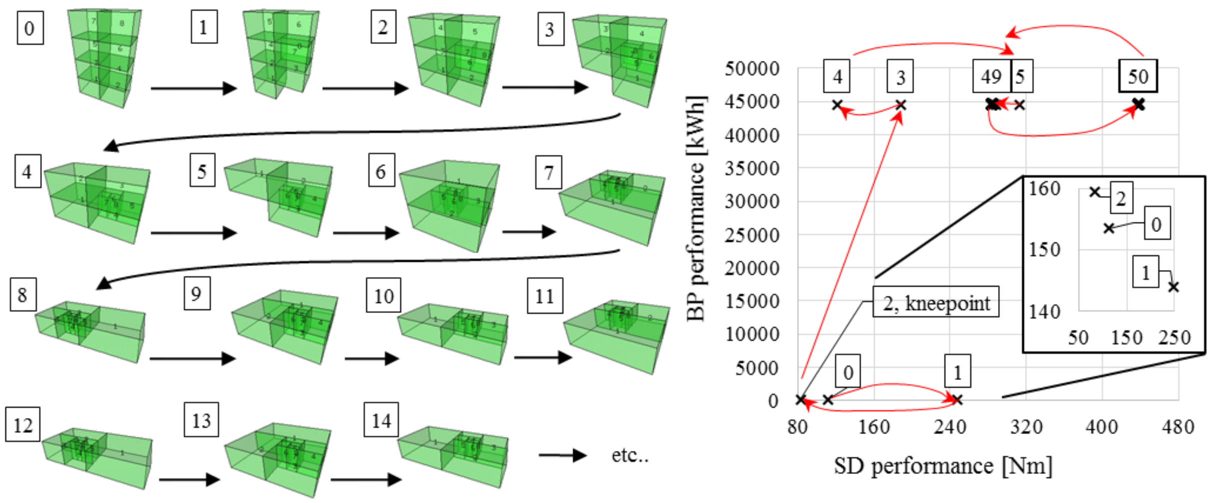


Figure 4: Designs along the design path of the CD only run, the knee point is found after the second iteration. The algorithm starts oscillating around solutions 7 to 10 after the sixth cycle. Note that each visualised design on the left of this figure is the final product of a single CD cycle.

Results for the SMS-EMOA run are shown in figure 5, two characteristic aspects can be noted. Firstly, at a 1000 evaluations the algorithm is not fully converged yet, as can be observed from the figure and from the irregular Pareto front. After 5000 evaluations, the Pareto front seems to have converged better, but it also shows that in a relatively late stage the algorithm found an improved solution space for the thermal design objective which has not fully been investigated yet. Secondly, the empty supercube cells at the top of the visualised designs indicate that better solutions could be obtained if more cells in the $x$- and $y$-directions were available, since this suggests that high buildings are non-optimal in this case study. On a general note, it should be mentioned that some tall slender spaces appear in the found design solutions. This is allowed for this case study but could be prevented by introducing constraints for either minimum floor surface or maximum aspect ratios of space dimensions.

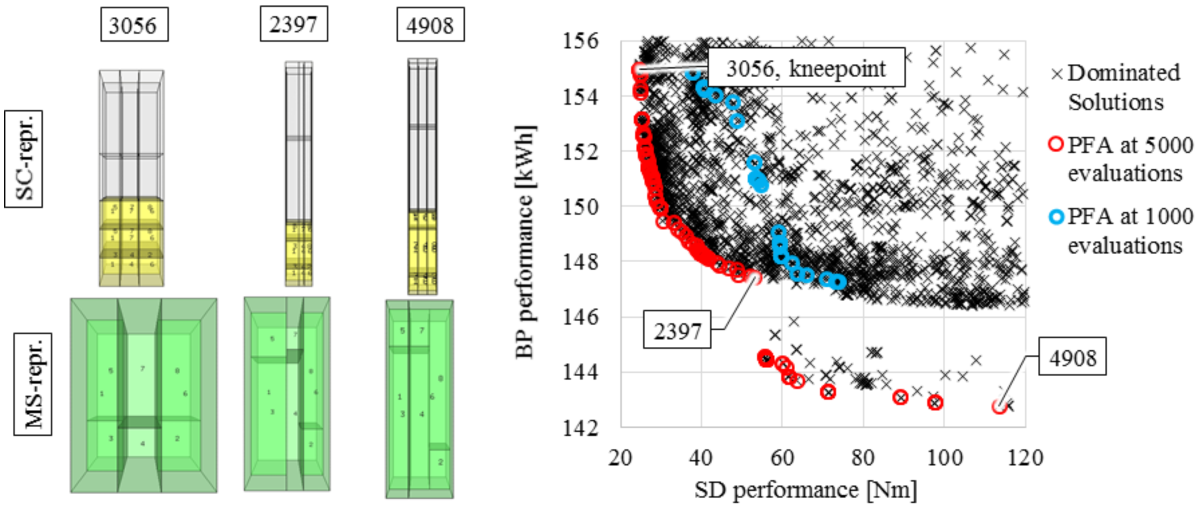


Figure 5: Results from the SMS-EMOA run. Some characteristic solutions are visualised on the left.

The combined method's results are presented in figure 6. The graph showing the Pareto fronts of the SMS-EMOA run in each iteration (figure 6, top) illustrates that only the first and fifth iteration of the combined method contribute to the eventual Pareto front approximation. This could be caused by the growing supercube size, since SMS-EMOA needs more evaluations to converge the PFA when a super-structure contains more solutions. The iterations with a larger supercube appear to be less converged judging by irregular Pareto fronts and the obviously non-optimal solutions. Moreover, it can be observed that the chosen design selection is sensitive to outliers in the results. Outliers in the BP performances of this case study are also considered in the computation of the knee points, therefore a preference for selection of SD optimal solutions (top left of PFA's) occurs. Additionally, the first run of SMS-EMOA has been continued an extra 4000 evaluations, this run shows that CD can find design search spaces that contain better solutions. Finally, comparing the total results of the run of the combined method with 5050 evaluations with the single run of SMS-EMOA after 5000 evaluations it can be seen that the PFA of the single SMS-EMOA run is extended with the part of the PFA of the combined run.

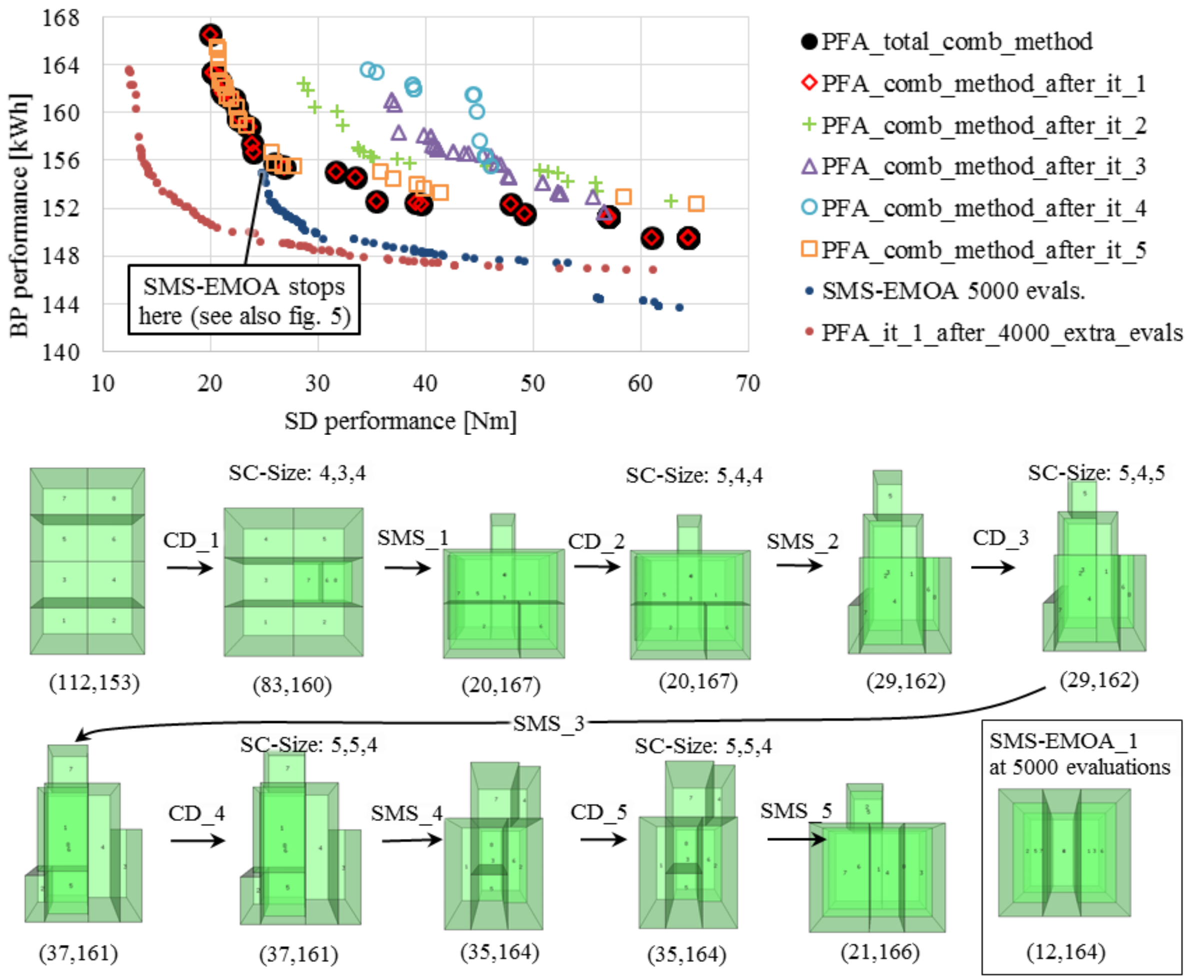


Figure 6: Top: Graph showing the Pareto front approximations after each combined method iteration and for comparison the single SMS-EMOA run with 5000 evaluations. Bottom: The path of the combined method, i.e. selected designs (knee points) after each optimisation run.

### 3.3 Discussion

The results show that the combination of methods proves to be able to suggest better design search spaces. It should however be noted that the presented results are a demonstration and somewhat arbitrary. For example, they are generated by a probabilistic algorithm and therefore new runs may not produce the same results. Additionally, SMS-EMOA has been tuned for different settings, namely for five spaces rather than eight and also for a different building thermal design objective. More tuning and experience should give more insight in the number of required evaluations for SMS-EMOA in the combined method. Moreover, the CD method has been presented using only one set of modification rules. Adding diversity to the rule set for modification will allow CD to explore multiple directions and steer towards Pareto optimality.

Comparing the results of the single SMS-EMOA run with the total results of the combined method it can be concluded that the combined method did not find improved solutions (with the exception of a slightly improved SD objective). Nevertheless, the 4000 extra evaluations of SMS-EMOA after the first iteration of the combined method prove that at least after the first CD run a better design search space has been found.

Currently no limitation on supercube size in the SMS-EMOA method is implemented, but it might be advantageous to constrain this size. The reason would be that larger problem sizes need more time to search for solutions and would thus have a slower convergence. Limiting the size leads to faster convergence, this will improve the performance of the combined method when the design selection and the CD methods are configured as such that they can select sub-design search spaces effectively.

## 4. Conclusion and Outlook

Three optimisation methods have been introduced: a super-structured; a super-structure free; and a hybrid method. The hybrid optimisation method has been explained, and its different schemes and new optimisation parameters were identified. A case study has been presented to demonstrate and compare the three optimisation methods. The co-evolutionary design method can quickly find better solutions, however, it is also prone to erratic behaviour. SMS-EMOA can find good Pareto front approximations within its design search space, but it cannot find better design search spaces. The combined method proves that the CD method can indeed shift the design search space of a super structured approach. It was shown that newly selected design search spaces can contain improved solutions, however this is dependent on the effectiveness of the used CD method(s).

The presented research is promising, and in the future, it may provide a method for designers that can quickly give insight in design problems. There is however still research to be carried out: A diversity in CD methods will be developed to offer the ability to steer solutions towards different parts of the Pareto front. An extensive investigation into parameter combinations with different case studies should provide more insight and experience with the hybrid method. Diversity maintenance in SMS-EMOA when initialised with a priori defined solutions will be investigated. Finally, hypervolume-based subset selection will be considered for design selection.

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