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A comparison between sequential and simultaneous whole-building design optimization for building performance

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Abstract

This paper compares the effectiveness of a sequential and a simultaneous approach, respectively derived from a conventional and an integrated whole-building design process, in the optimization of building geometry, fabric, HVAC system and its controls for building performance. It provides insights regarding theoretical benefits and limitations of the two approaches respectively based on a stage-by-stage or integrated optimization process and their comparative evaluation through a case-study office building nominally located in Nottingham (UK), modelled in Grasshopper for Rhino and simulated through EnergyPlus engine. The authors utilized a full-factorial (exhaustive) search method to explore the design space, therefore ensuring the optimality of the solutions. The resulting set of design options are postprocessed to identify Pareto-optimal designs that minimise energy demand while ensuring occupants' thermal comfort. 12 combinations of tests have been performed based on the initial values & the order sequence of the design parameters, and eventual grouping of variables pertaining to the same building element category. It has been found that, despite the theoretical advantages of a simultaneous building optimization approach outperform any adequate design optimization effort during individual decoupled phases, the sequential search run forward and starting at the variables' upper bound can find the same amount of Pareto-optimal solutions obtained from a simultaneous optimization while guaranteeing their "global" optimality.

Introduction

The mounting energy and environmental impact concerns are forcing many countries to adopt policies with stringent criteria for both new and refurbished buildings (EIA, 2020). In response, high-performance building design is increasingly becoming the object of interest of multi-disciplinary building stakeholders seeking the improvement of a wide variety of environmental goals (Mollaoglu-Korkmaz et al., 2012).

The design of high-performing buildings is a complex task since it heavily relies on inter-disciplinary knowledge with interacting and highly constrained inter-dependent factors, and often conflicting design goals. Additionally, building design is a multi-element process, spanning from architectural design (building geometries and fabric design) to the HVAC system selection, design and sizing, and their controls. This results in a large number of candidate design options which requires the design team to identify, evaluate and select the solutions satisfying the design goals, constraints and the team vision through an informed decision-making process.

In this context, computational methods of design optimization offer great potential in solving design challenges, overcoming the long computational time of performance evaluation of candidate design solutions when using conventional Building Performance Simulation (BPS) (Ostergard et al., 2016). Specifically, a simulation-based multi-objective optimization approach is suitable to high-performance building design to enhance decision-making through a robust resolution of highly complex design parameters interactions and trade-offs between conflicting objectives.

Buildings are conventionally designed following a step-by-step design process in which the output of the architectural design options (building morphology, façade geometries and fabric elements) develops into the input of the energy systems considerations (HVAC systems and controls). The "conventional" design process (CDP) typically involves building stakeholders in separate and sequential design stages. Therefore, if an optimization process mirroring the CDP were to happen, it would be based on individual optimization processes occurring at each design step, resulting in passing fixed "optimum" solutions to the next stage.

In the last ten years, a design paradigm called "integrated" design process (IDP) has gained increasing interest among building practitioners (Karlessi et al., 2017). The IDP disrupts the conventional (and sequential) building design workflow by involving building stakeholders at the same time in a collaborative environment (Kanters and Horvat, 2012). If an optimization process mirroring the integrated design steps were to happen, it would merge the individual optimization processes into a holistic task, a joint optimization process of building design elements resulting in global "optimum" solution.

Although recent studies have explored the potential of integrated optimization approaches, they focused on building energy demand and supply (Ferrara et al., 2019; Waibel et al., 2019) in a two-stage process. It is however non-trivial to investigate the effectiveness of an optimization process mirroring a conventional and an integrated approach in the holistic design of buildings for optimal performance.

This work is intended as an exploratory comparison between a sequential and a simultaneous design approach in the optimization of building geometry, building fabric, HVAC system and its controls for building performance. It provides insights regarding (1) theoretical benefits and limitations of the two optimization approaches and (2) their evaluation through a case-study building.

The sequential and simultaneous whole-building design optimization processes

Buildings are conventionally designed following a sequential and iterative step-by-step process in which client, architect, and engineer are separately involved in pre-defined tasks to complete at each stage. During the pre-design phase, the goals and baselines are set by the whole design team according to the client's requirements. Architectural design alternatives are then explored by the architect during the conceptual design phase. The design development consists of the discussion of building fabric options by the architect team, followed by the HVAC system design and sizing by the engineering team and control type selection during operation. It is evident how the conventional (and sequential) design process relies on output-input relationships since the information passing between each stage are almost fixed and constitute the input for the definition of the subsequent stage, this being the output of the previous one. Additionally, since the energy systems are often a plug-in at the end of the design development, the engineers need to seek the integration with the architectural design achieved during the previous design stages. This process might not produce satisfactory results during the first attempt, requiring a cyclical feedback-adjustment loop of design modifications from the architectural and engineering team to produce an efficient building and system design by reaching a feasible design option ensuring the load balance of the building (Flager and Haymaker, 2009).

As portrayed in Figure 1, if an optimization process mirroring the CDP were to happen it would occur in separate stages, splitting building design process into individual domains.

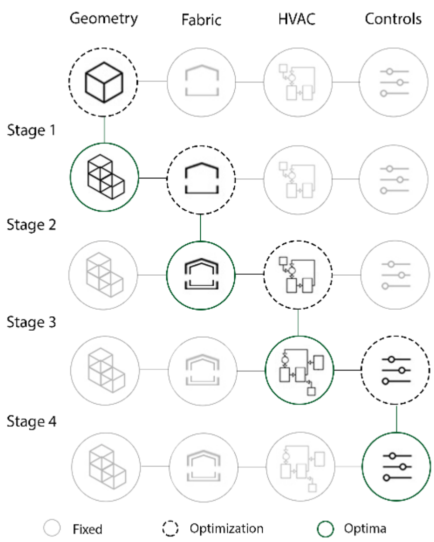

Figure 1: Sequential building design optimization.

The optimization would then consider building elements in isolation diminishing the opportunities for synergies between building elements and failing to consider the complex interactions that would result. Based on input-output relationships, a separate optimization process would take place at each design step, passing "optimal" solutions to the next stage, while the remaining building elements are fixed on a baseline scenario.

If the optimization is multi-criterion, then multiple solutions can be carried forward between stages of the sequence. The optima from each stage, determine the variable values for the next stage of the search. This results in a limited number of design possibilities explored since the scanning of the feasible options would be restricted by the solutions judged "optimal" through the previous stages, not covering all the other feasible options. The optimization would also compromise the iterative feedback-adjustment loop involving energy systems and architectural options. In fact, the engineer will have to select and size the HVAC system and controls based on "optimal" building morphologies and fabric, without the possibility of giving feedback to the architectural team for adjustments. This might affect the integration between building geometries & energy system and could compromise building performances, system effectiveness or the feasibility of implementation. The limitations of the sequential approach are also evident if it is acknowledged that an optimization process is only able to find "optimal" solutions for the defined problem. As illustrated in Figure 1 at stage 1, the building fabric, system type, and control strategy are fixed. The impact of this is that the geometry is only "optimal" for these defined building elements; if they are changed, then it is plausible that the geometry will no longer be "optimal". Although at stage 2, the optimized geometry, becomes one of the fixed conditions, since the optimality of the geometry is only valid for the previously defined fabric, it cannot be guaranteed that a new solution to the choice of fabric is found, or that it is more "optimal".

In the last ten years, a design paradigm which integrates the knowledge gained through the application of the CDP into a new systematic process for design practice has gained increasing interest among building practitioners (Karlessi et al., 2017). The fundament of the "integrated" design process (IDP) is based on the observation that changes and improvements during the building design process are relatively easy to make at the beginning but become increasingly difficult and influential as the process unfolds. For this reason, the IDP disrupts the sequential building design workflow by involving building stakeholders early in the design process in a collaborative environment (Kanters and Horvat, 2012). Once baselines and goals are defined during the pre-design phase by the whole design team according to the client's requirements, the architect can explore architectural design decision in collaboration with the engineer analyzing HVAC systems and control strategy according to the building energy demand and pattern zone loads.

This interlaces the disciplines that inform the building design process resulting in a synergetic approach towards design solutions. In fact, the HVAC equipment and controls are not selected and designed complementary to the architectural design but as a joint discussion of alternatives early in the design process. As shown in Figure 2, if an optimization mirroring the IDP were to happen it would occur as a joint task, merging building design elements. The optimization would then consider buildings in a holistic-thinking perspective, enhancing the opportunities for synergies between building elements and the consideration of the complex interactions that would result. The search among a large amount of design options during a single optimization run cyclically weights the solutions exploring the various options of each building design element.

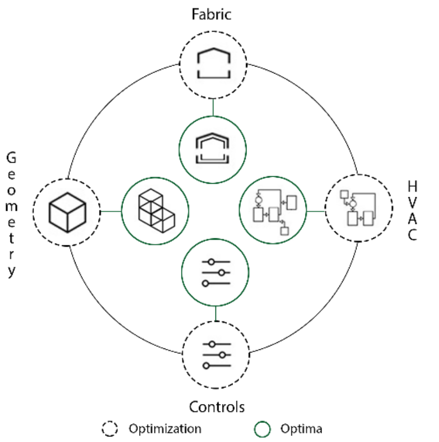

Figure 2: Simultaneous building design optimization.

The consequence is an extensive scanning of design potential through the solution space explored, potentially leading to “global optimum” solutions. Moreover, a simultaneous optimization could enhance the iterative feedback-adjusting loop involving architectural options and energy systems. Additionally, it could allow to find the optimum combination of variable values that influence the building energy fluxes since the variables are considered jointly and simultaneously. Although the simultaneous approach has several benefits, due to the large number of iterations required, it may suffer from a long computational time. Furthermore, while the simultaneous approach could yield “globally optimal” solutions, can the sequential search find the same number of Pareto-optimal solutions while guaranteeing their “global” optimality? If not, are they considerably “worse” in terms of building performance? This paper seeks to answer these questions through the methodological approach described in the next section.

Methodology

The methodological approach consists of the evaluation and comparison of the two optimization approaches. The evaluation begins with the (1) problem formulation where optimization objectives, constraints, variables and perturbation values are selected, followed by their (2) implementation within a thermal model. Subsequently, a (3) search method generates the sets of solutions and (4) finally the results are post-processed to identify Pareto-optimal solutions for each experiment and compared.

Problem formulation

The study in this paper is based on 2 building performance metrics as optimization objective functions: (1) the total heating energy demand (kWh) expressed as the sum of the energy consumption of HVAC components, and (2) the occupant’s thermal comfort indicated by the uncomfortable hours. Fanger’s PMV (Predicted Mean Vote) model (Fanger, 1970) is used to assess the indoor environment of the building during the occupied conditioned period, with the uncomfortable hours indicating the period of time outside the PMV range of +/-0.5. The two criteria are to be minimized. Figure 3 illustrates the design parameters and their perturbation values grouped by building element, derived from building standards, engineering & design practice guidebooks and real-world considerations.

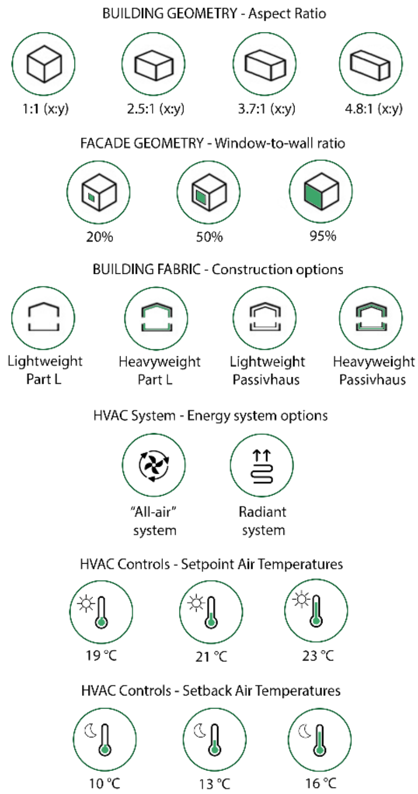

Figure 3: Variables options and respective values.

In an effort to limit the computational load, the design space comprises six design variables, selected due to their effect on the design criteria and pertaining to each of the analyzed building elements: aspect ratio (building geometry); window-to-wall ratio (façade geometry); building fabric options; HVAC system options; heating setpoint and setback air temperature (controls).

The 4 selected options of aspect ratio controlling the building geometry are based on an incremental value in envelope wall area (+10% each option) while keeping the building volume fixed. Therefore, from a square building with 1:1 ratio, each option represents a proxy for the increasing amount of heat gains and losses in a building through the linearly increasing exterior wall area. The window-to-wall ratio (WWR) controls the percentage of opaque and transparent façade and ranges from a predominantly opaque façade (20% WWR) to a fully glazed one (95% WWR with a 5% extra being the mullions area) and a medium value of 50%. Regarding the building fabric, 4 types have been selected based on Wright et al. (2016): two options complying with the Approved Document L2A of the UK Building Regulations for new buildings other than dwellings (UK Government, 2013) and the remaining two options with the Passivhaus Standard (Mead and Brylewski, 2010). The two options in compliance with each building standard have similar U-values but different thermal weights (heavyweight (HW) concrete and lightweight (LW) timber constructions), this helping to assess the impact of thermal mass on optimum performance. However, in this contribution, each option comprises all building constructions altogether as an entire system (glazing, walls, and roof). Table 1 breakdowns the U-values of the building assemblies.

Table 1: U-values of building assemblies' options.

	U-value (W/m²K)			
	Part L document		Passivhaus	
	LW	*HW*	*LW*	*HW*
Walls	0.394	0.360	0.150	0.143
Roof	0.262	0.253	0.151	0.149
Floor	0.253		0.253	
Windows	1.4		0.7	

The two HVAC system options analysed are a radiant system, which meets more than 50% of the total space heating load through thermal radiation, and a conventional "all-air" conditioning system, instead mainly based on convection. Specifically, a floor Embedded Surface System (ESS) has been designed for sensible heating while a Dedicated Outdoor Air System (DOAS) with a plate heat recovery system is in place for humidity control and contaminants removal. The "all-air" system designed is a Constant Air Volume (CAV) system for both sensible and latent loads with fixed fan speed and a plate heat recovery system. Heating setpoint and setback values have been defined based on CIBSE Guide A (CIBSE, 2006), adopted as design variables since they drive the trade-off between energy demand and thermal comfort. Three values have been assigned to each variable representing an average scenario of 21 ˚C setpoint and 13 ˚C setback, and a cooler (19 ˚C setpoint and 10 ˚C setback), and warmer scenario (23 ˚C setpoint and 16 ˚C setback).

Implementation

The coupling of parametric modelling, building performance simulation (BPS) and optimization approach allows the definition, self-automated simulation and data generation of a case-study building exploring candidate building geometries, fabric, HVAC systems and controls options. A computational framework has been developed in Grasshopper for Rhino (McNeel, 2012), a user-friendly visual programming software for modelling. Its main interface has been utilized to define the building and envelope geometries. Ladybug and Honeybee plug-ins translate the geometries into thermal zones assigning custom material assemblies, zone loads, programs and occupancy patterns. Additionally, it is adopted as an umbrella for the building performance analysis utilizing Energy-Plus engine and OpenStudio capabilities. Ironbug plug-in allows to design customized HVAC systems and controls and assigns them to each thermal zone. Finally, TT Toolbox plug-in links variables and objectives and automates the search process launching the sequence of simulations, recording every iteration and storing the solutions in csv format, represented as strings of values for each simulation in which the set of variables changes corresponds to the performance values obtained. Figure 4 depicts the case study building: a ground-level medium-size office nominally located in Nottingham (UK), featuring a 100 m^2 open-space with a floor to ceiling height of 2.7m. Each façade has an operable ribbon window without any internal or external shades.

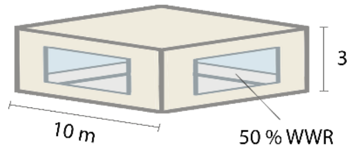

Figure 4: Example configuration of the modelled case study office building.

The Test Reference Year (TRY) provided by CIBSE (2009) is used as weather file to ensure the compliance with the UK Building Regulations Part L (UK Government, 2013). Occupancy patterns are distributed between 7:00 and 17:00, 5 days per week. The zone has typical design conditions of 1 occupant per 10m2 floor area and equipment loads of 12 W/m2 floor area. Maximum lighting loads are set at 8 W/m2 floor area, with a dimming daylighting control with a setpoint of 500 lux at a reference point located in the middle of the space. Infiltration is set at 0.1 air changes per hour, and ventilation is provided at a constant rate of 0.01 m3/s, this being equivalent to 10 l/s per occupant at full occupancy. The radiant floor heating start-time control is set two hours before occupancy to allow the system response time to meet the setpoint while the CAV start-time is set one hour before occupancy; free-cooling is available through natural ventilation during the summer period.

Search method

Building optimization problems are most frequently solved using population-based metaheuristic search methods, such as evolutionary and particle swarm algorithms (Evins, 2013; Ekici et al., 2019). A characteristic of these algorithms is that they use probabilistic search operators, the parameters of which require careful tuning if consistent convergence onto the optima is to be obtained (Alajmi and Wright, 2014). The probabilistic nature of the algorithms also results in different solutions being found across repeated runs of the search (Hamdy et al., 2016). In contrast, a full-factorial (exhaustive) search does not require tuning and is guaranteed to identify all optima. The generation of an exhaustive set of solutions, also allows a range of optimization experiments to be performed without the need to re-simulate the building performance for each experiment (a set of three different experiments being performed in this study).

Solution Analysis

The resulting set of solutions containing combinations of design options and corresponding objectives values are post-processed with the help of programming based on a simultaneous and a sequential approach. That is to say, considering simultaneously the building elements while searching for optima within the whole set of resulting design combinations (Figure 2) or addressing the building elements individually and sequentially searching for optima within each set. In fact, the sequential approach searches for optima from each design element while keeping the others on a baseline scenario during a one-at-a-time staged process in which the optima from the previous stage become the input of the subsequent one (Figure 1). Three series of experiments have been performed to evaluate the sequential approach, giving 12 combinations of tests: analysis on the initial values of the design parameters used at the start of the search (low bound, middle range and upper bound base points), analysis on the order of the sequence of variables during the search through a conventional approach (forward: geometry > fabric > HVAC systems > setpoints), and a test approach (reverse: setpoints > HVAC systems > fabric > geometry) mimicking the adoption of a dynamic programming approach, and eventual grouping of variables pertaining to the same building element category (with grouping: geometry [aspect ratio, WWR], fabric, HVAC system and controls [setpoint, setback], and without grouping. The optima and sub-optima are achieved through the Pareto ranking of the solutions as trade-offs between the evaluated objectives, and the resulting sets of design solutions pertaining to each optimization approach are analysed highlighting the number of final optima, their optimality, and the direction of the search within the design space.

Results and Analysis

Simultaneous optimization approach

Figure 5 portrays the set of solutions of the simultaneous search highlighting the dominated and the Pareto-optimal solutions. The simultaneous optimization found 9 "global" optimal solutions as trade-offs between energy demand and uncomfortable hours. The Pareto set shows a significant discontinuity in the solutions having split fronts. 7 solutions lie on the first Pareto front characterized by low energy demand while 2 solutions can be considered "outliers" characterized by increased energy demand but with a lower number of uncomfortable hours.

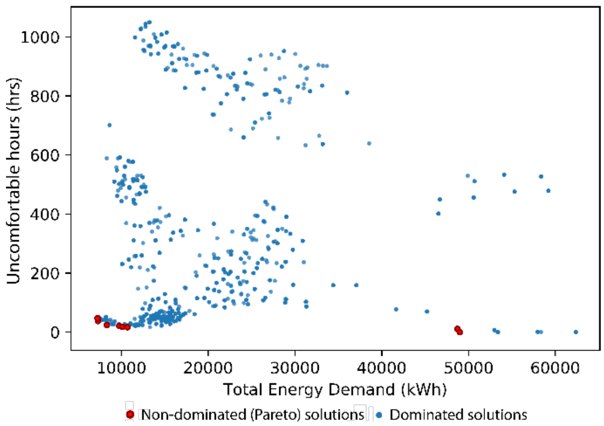

Figure 5: Trade-off solutions between uncomfortable hours and energy demand of simultaneous optimization.

Sequential optimization approach

Figure 6 displays the set of solutions of the sequential approach for each experiment performed. Different coloured symbols (shape outline) show how the search progresses for each building element, highlighting the Pareto-optimal solutions (shape filling). Table 2 summarizes the experiments conducted and their results illustrating the set of solutions identified and their corresponding variables and objectives values. The following paragraphs detail the analyses for each experiment.

The sequential optimization approach run forward and starting at the variables' upper bound can find the same amount of Pareto-optimal solutions obtained from a simultaneous search while guaranteeing their "global" optimality. In fact, both the grouped and ungrouped searches found 9 optima solutions. As depicted in Figure 6, two sets of solutions are carried forward from the fabric and HVAC system stages to form the final optima solutions of the grouped search with the remaining five being found during the setpoints optimization, while one solution has been carried forward from the fabric stage for the ungrouped search with two other sets from the HVAC system and setpoint optimizations to form the final optima solutions. The remaining four solutions are found during the setback search.

It can be observed that the number of optima found changes depending on the variables' starting point. The forward-grouped search starting at the low bound found 7 optima solutions in split fronts. As portrayed in Figure 6, the same sets of solutions have been judged optimal during each stage until the last one, where only one optimum from the fabric stage is contained in the final Pareto-optimal solution set. The optima are the same that have been obtained through the simultaneous optimization with the two missing ones being the high energy demand solutions. Since the "outliers" result in a significant discontinuity in the Pareto front, this might contribute to the reason for them not being found in the sequence.

Both the forward grouped and ungrouped searches starting at the middle bound found 3 optima solutions in split fronts. As depicted in Figure 6, only one optimum from the design stages is contained into the final Pareto solution set of the forward-grouped search brought over from the HVAC system optimization, while one Pareto-optimal for the forward-ungrouped search is brought over from the HVAC system and one from the setpoint optimization stages. All 3 solutions from the forward grouped and ungrouped searches are found in the simultaneous search as well.

Generally, the reverse sequential search found less "globally" optimal solutions than the forward, regardless of the variables' starting point. Additionally, for both the forward and reverse search, grouping has a little effect. In fact, the reverse-grouped search starting at a low bound found 5 solutions. As portrayed in Figure 6, all the final optima are carried forward from previous stages, with three solutions since the first stage while the remaining two from the fabric optimization. Four solutions [288, 384, 768, 780] out of five [300] are "globally" optimal.

Both the forward and reverse searches starting at a low bound found 5 optima solutions in split fronts. One solution has been judged optimal since the first stage while other two sets are carried forward from the WWR and the HVAC system optimization stages for the forward-ungrouped and from the fabric and HVAC system stages for the reverse-ungrouped. Two solutions [288, 384] are "globally" optimal while other 3 [300, 480, 492] were not found during the simultaneous search.

Both the reverse grouped and ungrouped searches starting at a middle bound found 4 optima solutions in split front. As shown in Figure 6, none of the final Pareto solution was found during the previous stages but they were judged optimal during the last design stage. 2 solutions found from the reverse-grouped optimization are "globally" optimal [12, 288], while other 2 solutions [0, 192] were not found in the simultaneous search. 2 solutions [288, 384] out of 5 [300, 480, 492] are "globally" optimal.

Both the reverse grouped and ungrouped searches starting at an upper bound found 4 optima solutions. As illustrated in Figure 6, none of the final Pareto solution was found during the previous stages but they were judged optimal during the last design stage (controls optimization for grouped search and setbacks for the ungrouped one). 3 solutions found from the reverse-grouped optimization are "globally" optimal [288, 768, 780], while one [108] was not found during the simultaneous search. 2 solutions [684, 780] out of 4 [576, 672] found from the reverse-ungrouped optimization are "globally" optimal.

Discussion

It has been observed that, in a sequential search, the ability of finding the correct amount of Pareto-optimal solutions while guaranteeing their "global" optimality due to the exhaustive exploration of the solution space are significantly affected by the initial values and the order sequence of the design variables. The impact of variables grouping within building element categories can instead be considered negligible. Out of 12 experimental runs, two sequential searches mirrored the results obtained by a simultaneous optimization, these being the forward grouped and ungrouped starting from the variables' upper bound. Additionally, while the total number of solutions found within each sequence order is similar, the reverse searches show that almost half of the Pareto-optimal solutions are not "globally" optimal.

It has been found that the direction of the search is influenced by the initial values of the variables adopted at the start of the search. In fact, starting from the lower bound, initialises a sequence that is close to the the final Pareto set, which moves further away during the search and returns close to the initial optima to form the final solutions, while starting from a middle-range or upper bound initialises a sequence far from the final Pareto which is progressively reached with each iteration stage-by-stage.

Independently on the characteristics of the experiment performed, this research found a correlation between the number of optima carried forward from previous stages and number of the final Pareto solutions. The more solutions are able to "survive" through each stage, the highest is the number of final optima identified. In fact, searches with up to 4 final Pareto-optimal solutions identified, generally show that different sets of solutions are judged optimal at each stage of the search or a low number of final optima soluttions are carried forward, while searches with a higher number of final optima (from 5 to 9) show that at lest half of the final solutions are carried forward from previous stages.

Overall, the Pareto-optimal solutions found during the sequential search that were not "globally" optimal, showed performance metrics values very "close" to the "global" optima set. Regarding the variables, only one building geometry has been selected: a square building with 1:1 aspect ratio. Among the "globally" optimal solutions set, the two outliers have a fully glazed façade while the others include a 20% WWR; 10 other geometry combinations are sub-optimal. All the optima from the sequential searches instead exhibit a 20% WWR. The 2 building fabric options identified are the constructions complying with Passivhaus standard with and without thermal mass, while 2 other wall assemblies are sub-optimal. The "globally" optimal solutions include both HVAC system options however the first 7 solutions adopt radiant heating while the 2 outliers include an all-air system. All the optimal solutions obtained from the sequential searches adopt radiant heating. Optimal setpoints and setbacks include 7 of the possible 9 combinations.

Since there is no change in building shape across the solutions, the aspect ratio can be considered a "distance" variable that governs the distance of the final optima from the true Pareto front while determining how close to the Pareto front a solution lies (Brownlee and Wright, 2012). In fact, changing the aspect ratio, would move the final optima back from the true Pareto front. The window-to-

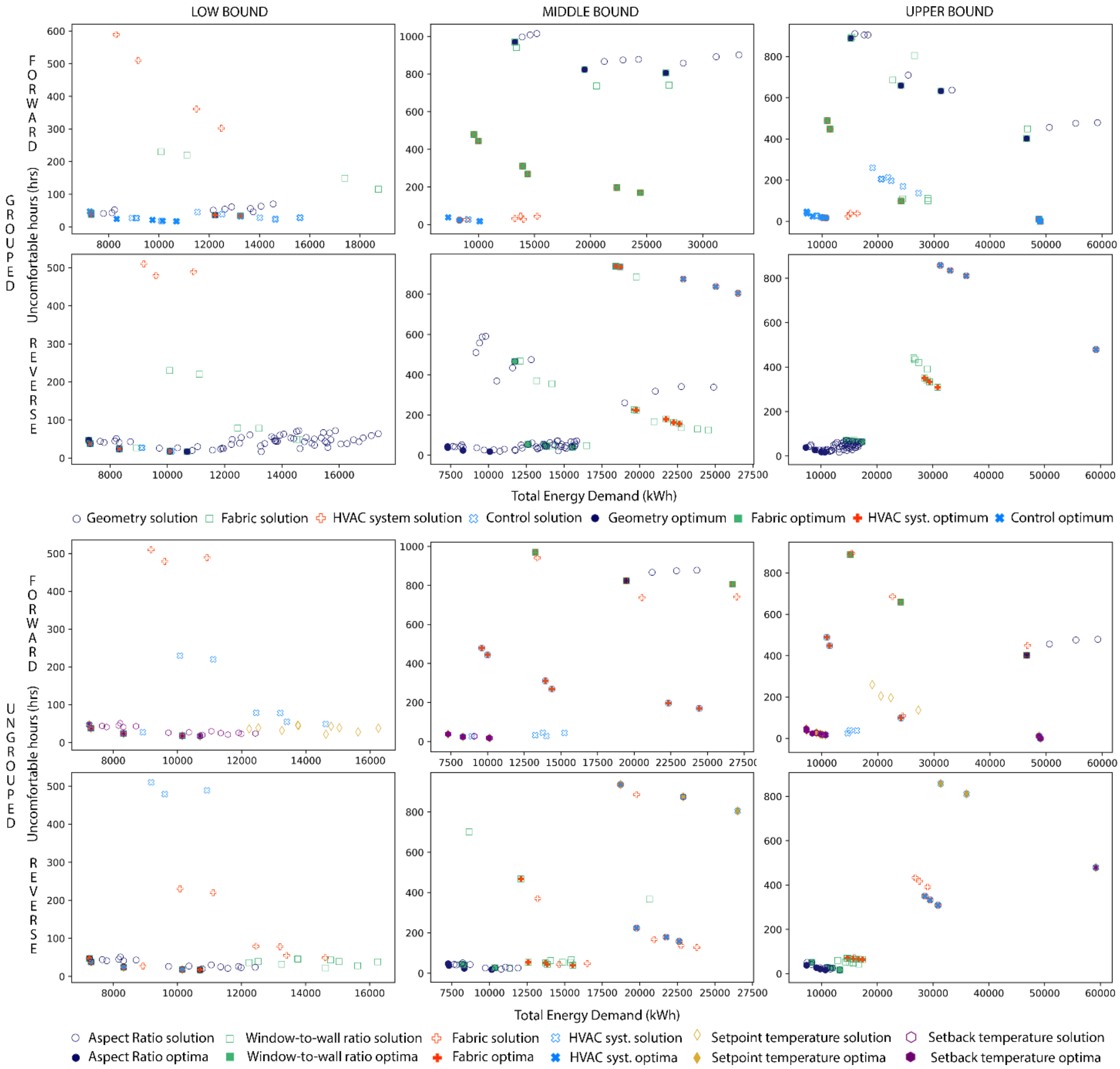

Figure 6: Trade-off solutions between thermal comfort and energy demand of sequential optimization.

Table 2: Summary of experiments with sets of Pareto-optimal solutions and corresponding objectives values

Index	Design Variables						Performance metrics		Simultaneous Optimization	Sequential Optimization													Frequency
	Geometry		Fabric	HVAC	Controls		Energy	Th. Comfort		Forward						Reverse							
	Shape	Façade			Occupied	Unoccupied				Grouped			Ungrouped			Grouped			Ungrouped				
	Aspect Ratio	Window-to-wall ratio (%)	Fabric type	Energy System type	Setpoint Temp. (°C)	Setback Temp. (°C)	Energy Demand (kWh)	Uncomfortable hours (hrs)		Low bound	Middle bound	Upper bound	Low bound	Middle bound	Upper bound	Low bound	Middle bound	Upper bound	Low bound	Middle bound	Upper bound		
588	1	20	LW_PH	Radiant	19	16	7247	47															3
12	1	20	LW_PH	Radiant	19	10	7302	43															4
288	1	20	HW_PH	Radiant	19	13	7304	38															10
384	1	20	HW_PH	Radiant	21	13	8319	24															10
684	1	20	LW_PH	Radiant	21	16	9745	21															4
768	1	20	HW_PH	Radiant	23	16	10088	18															7
780	1	20	LW_PH	Radiant	23	16	10688	17															6
548	1	95	LW_PH	Air	23	13	48726	11															2
824	1	95	HW_PH	Air	23	16	48981	0															2
300	1	20	LW_PH	Radiant	19	13	7253	47															4
0	1	20	HW_PH	Radiant	19	10	7307	38															1
576	1	20	HW_PH	Radiant	19	16	7313	38															1
108	1	20	LW_PH	Radiant	21	10	8920	27															1
672	1	20	HW_PH	Radiant	21	16	9083	27															1
192	1	20	HW_PH	Radiant	23	10	10095	18															1
480	1	20	HW_PH	Radiant	23	13	10150	18															3
492	1	20	LW_PH	Radiant	23	13	10703	17															2
							Optima		9	7	3	9	5	3	9	5	4	4	5	4	4		
							"Global" Optima		9	7	3	9	2	3	9	4	2	3	2	2	2		

Solution found   Solution not found

wall ratio in combination with the energy system type, are "position" variables with the change in their value driving the change in objectives values along the Pareto front. In fact, the result of their variability is a significant increase in energy demand when the window-to-wall ratio assumes values of 20% or 95%, in combination with the change in system type from radiant to all-air system. The setpoints are the predominant "position" variables driving the change in energy demand and thermal comfort.

Conclusion

This contribution presents an exploratory comparison between a sequential and a simultaneous design approach in the optimization of building geometry, building fabric, HVAC system and its controls for building performance. The building model with the selected variables and therefore the scale of the search, are restricted to the scope of this contribution which is intended as a first evaluative step. It has been found that, despite the theoretical advantages of a simultaneous building optimization approach outperform any adequate design optimization effort during individual decoupled phases, the sequential search run forward and starting at the variables' upper bound can find the same amount of Pareto-optimal solutions obtained from a simultaneous optimization while guaranteeing their "global" optimality. Additionally, the Pareto-optimal solutions found during the sequential search that were not "globally" optimal, showed performance metrics values very "close" to the "global" optima set. Further research is needed to gain additional understanding on the effectiveness and reliability of a simultaneous and a sequential approach. Insights on the interactions between building design elements and their dependencies as well as the study of computational performances will be drawn by increasing the granularity of the problem formulation and testing with a tuned genetic algorithm.

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