Multi-criteria robustness assessment of a sequential whole-building design optimization

Riccardo Talami, Jonathan Wright, Bianca Howard
School of Architecture, Building and Civil Engineering, Loughborough University, Loughborough, United Kingdom.

Abstract
This paper assesses the reliability of a sequential approach, derived from a conventional design process, in the optimization of building geometry, fabric, HVAC system and its controls for building performance. In this study, the reliability is defined as the ability of the approach to find all Pareto-optimal design solutions under scenario-based uncertainties on occupant behaviour and weather conditions. The optimization criteria are the minimization of energy demand and warm discomfort hours. A full-factorial (exhaustive) search method has been adopted to explore the design space, therefore ensuring that all Pareto-optimal solutions are identified and used a benchmark for the sequential search. Eight combinations of tests have been performed based on different initial values and groups of the design parameters used at the start of the sequential search. It concluded that a sequential search, across scenarios, identified, on average, 70% of the Pareto-optimal solutions obtained from a full-factorial search, with a computational saving of function evaluations of 99.99%. Additionally, the ability to obtain solutions displaying medium and high robustness is not affected by the lower frequency of optima found across scenarios.

Key Innovations
- Across scenarios, a sequential search identified, on average, 70% of the Pareto-optimal solutions obtained from a full-factorial search.
- A sequential search offers a 99.99% computational saving in terms of function evaluations compared to a full-factorial search.
- The lower frequency of optima found does not affect the ability of a sequential search to identify solutions with medium and high robustness.

Practical Implications
A sequential search appears to be a robust approach when considering uncertainties, offering computational savings compared to a full-factorial search.

Introduction
The ever-increasing necessity of designing high-performing buildings in response to the mounting energy and environmental impact concerns is set to enforce the practice of design exploration and computational methods of design optimization as part of the building design process (Machairas et al., 2014). In fact, high-performance building design is a complex multi-element and cross-disciplinary process, spanning from the architectural design (building geometries and fabric design) to the engineering domain (HVAC system design, sizing, and controls selection), which results in a large number of evaluations of candidate design options driving the often-conflicting goals of the building stakeholders.

In the context of design exploration in the design phase, Building Performance Simulation (BPS) tools predict the performance metrics, considering fixed assumptions over the entire building’s lifespan, formulated through educated guesses, or based on building guidelines and standards. Often, these assumptions have a significant impact on building performance and cause deviations between the predicted and operational performance (de Wilde, 2014). Furthermore, when coupling BPS with design optimization, the derived Pareto-optimal design solutions may prove to be non-robust if their optimality is compromised when uncertainty sources are considered (Nikolaidou et al., 2017). It is therefore important to include robustness assessment within the optimization process as a mainstream method during the design process to quantify the impact of uncertain factors on building performance (Tian et al., 2018).

He et al. (2020) classified the uncertainty in optimization problems in three types: (1) the disturbance added on decision variables, which imposes perturbations on decision variables, (2) the noise affecting the objective (fitness) evaluations and generates errors in performance estimation, and (3) the fluctuation of environmental parameters subject to varying environmental and operational condition. It is well understood that among the uncertain factors, the uncertainties associated with the “boundary conditions” are major factors that influence building performance (Tian et al., 2018). Although robustness can be assessed adopting stochastic or non-probabilistic approaches, the probability of occurrence of occupant behaviour and weather conditions is largely unknown over a building’s lifespan. For this reason, Kotireddy et al. (2018) suggest the adoption of a scenario analysis to perform robustness assessment, in which scenarios are implemented as alternatives with unknown probabilities.

The sequential whole-building design optimization
Buildings are conventionally designed following a sequential step-by-step approach based on input-output dependencies in which client, architect, and engineer are
separately involved in pre-defined tasks to complete at each stage, named “conventional” design process (CDP). 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.

By applying an optimization process mimicking the sequence dictated by the CDP, Talami et al. (2020) defined a sequential approach and gained initial insights on its behaviour. As portrayed in Figure 1, a sequential whole-building design optimization process is characterized by individual and sequential optimization processes taking place at each design step (aimed at the definition of one building design element), passing “optimal” solutions obtained from an exhaustive set of design combinations which restrict the number of design options of the next stage of the search (and consequently the search space), while the remaining building elements are not optimized but fixed on a baseline scenario to compute the objective function in a previous stage.

Methodology

The methodological approach consists of the robustness assessment of a sequential optimization approach. The evaluation begins with the (1) problem formulation where optimization objectives, constraints, variables, perturbation values, uncertain scenarios are selected, followed by their (2) implementation within a thermal model. Subsequently, a (3) search method generates the sets of solutions for each uncertain scenario, and the results are post-processed to identify Pareto-optimal solutions for each experiment. Finally, the (5) robust solutions are identified across scenarios and assessed according to their degree of robustness.

Problem formulation

The study in this paper is based on two 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 warm discomfort hours. Fanger’s Predicted Mean Vote (PMV) model (Fanger, 1970) is used to assess the indoor environment of the building during the occupied conditioned period, with the warm discomfort hours indicating the period of time above the PMV range of +0.5. The two criteria are to be minimized.

Research has discarded the potential of a sequential design optimization process in favour of simultaneous approaches (Bichiou and Krarti, 2011, Ferrara et al., 2019; Waibel et al., 2019, Gagnon et al., 2019). Additionally, they focused on building energy demand and supply in a two-stage process where the architectural elements were optimized sequentially to the energy systems (and eventually controls). This work enables for first reliability assessment of a sequential search mimicking a conventional design process in a four-stage approach, considering each building element (building geometry, fabric, HVAC system and its controls) as part of a single design stage, whilst accounting for occupancy, usage, and weather uncertain scenarios as a robustness indicator for the Pareto-optimal solutions.

Figure 1: The stages of a sequential whole-building design optimization process.

Table 1: Variables options and respective values.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Low</th>
<th>Middle</th>
<th>Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>Geometry</td>
<td>Shape</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Rectangle</td>
<td>L-shape</td>
<td>Free form</td>
</tr>
<tr>
<td>Fabric</td>
<td>U-value</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Baseline</td>
<td>+50%</td>
<td>+100%</td>
</tr>
<tr>
<td>HVAC</td>
<td>Distribution type</td>
<td>Radiant</td>
<td>Forced air</td>
</tr>
<tr>
<td></td>
<td>Plant type</td>
<td>Boiler</td>
<td>Heat pump</td>
</tr>
<tr>
<td></td>
<td>Supply water temperature</td>
<td>30 °C</td>
<td>40 °C</td>
</tr>
<tr>
<td>Controls</td>
<td>Setpoint temperature</td>
<td>19 °C</td>
<td>21 °C</td>
</tr>
<tr>
<td></td>
<td>Setback temperature</td>
<td>10 °C</td>
<td>13 °C</td>
</tr>
<tr>
<td></td>
<td>System start time</td>
<td>With occupancy</td>
<td>1h before</td>
</tr>
</tbody>
</table>

The design space comprises 11 design variables, selected due to their effect on the performance metrics and pertaining to each of the analysed building element: shape type, window-to-wall ratio, and building orientation (building geometry); building thermal mass and U-value options (building fabric); HVAC system distribution and

![Image](https://doi.org/10.26868/25222708.2021.30818)
The two HVAC distribution 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 Variable Air Volume (VAV) system for both sensible and latent loads with fixed fan speed and a plate heat recovery system. Each distribution type is applied to two HVAC plant system type: a conventional boiler and a ground-source heat pump. Three values of supply water temperatures have been assigned to represent an average scenario of 40 °C, with a cooler (30 °C), and warmer one (50 °C). 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). The system start-time options include (1) the system on when occupancy begins, (2) one hour before, or (3) two hours before occupancy.

Two boundary conditions are implemented as aleatoric uncertainty: occupant behaviour and weather conditions. Each of the uncertain “boundary” conditions has two uniformly weighted choices, giving a total of four uncertain performance scenarios (Table 3). High and low internal loads scenarios are formulated by varying occupancy schedules and occupant density, with the equipment and artificial lighting schedules and usage being varied in proportion. Two weather files for the same location provided by CIBSE (2009) are adopted to investigate the impact of changing climate and correspond to the test reference year (TRY) and a design summer year (DSY-2).

### Table 2: U-values of building assemblies’ options.

<table>
<thead>
<tr>
<th></th>
<th>LW</th>
<th>HW</th>
</tr>
</thead>
<tbody>
<tr>
<td>Walls</td>
<td>0.394</td>
<td>0.360</td>
</tr>
<tr>
<td>Roof</td>
<td>0.262</td>
<td>0.253</td>
</tr>
<tr>
<td>Floor</td>
<td>0.253</td>
<td></td>
</tr>
<tr>
<td>Windows</td>
<td>1.6</td>
<td></td>
</tr>
</tbody>
</table>

The low internal load scenario represents a lightly occupied office with a 25% occupancy rate during working hours (occupancy patterns distributed between 8:00 and 18:00, 5 days per week) and an occupant density of 0.06 ppl/m² at peak occupancy. This is reflected on a 25% usage rate of equipment and electric lighting with respectively an equipment load value of 6 W/m² representing a proxy for just a few laptops in each zone and 4 W/m² of lighting density controlled by a dimming daylighting control with a setpoint of 300 lux at a reference point located in the middle of the space. The high internal load scenario represents a packed office with a 100% occupancy rate during working hours and an occupant density of 0.2 ppl/m² at peak occupancy. This is reflected on a 100% usage rate of equipment and electric lighting with respectively an equipment load value of 15 W/m² representing an office filled with computers and 12 W/m² of lighting density due to all the available electric lights being always on during the occupancy period. The TRY weather file has been adopted to comply with the UK Building Regulations Part L (UK Government, 2013). The DSY-2 is typically used for overheating analysis, representing an extreme year characterized by a short and intense warm spell.

### Implementation

A computational framework has been developed in Grasshopper for Rhino (McNeel, 2012) coupling...
parametric modelling, building performance simulation (BPS) and a full-factorial search approach to allow the definition, self-automated simulation and data generation of a case-study building exploring candidate building geometries, fabric, HVAC systems and controls options. Its main interface has been utilized to define the building and envelope geometries, subsequently translated into thermal zones by assigning custom material assemblies, zone loads, programs and occupancy patterns through Ladybug and Honeybee plug-ins. Each zone includes a customized HVAC distribution system and controls linked to a plant system designed adopting Ironbug plug-in. Finally, TT Toolbox plug-in linked to Energy-Plus engine and OpenStudio capabilities automates the search process extracting the design combinations while generating the OSM files to run adopting a parallel computing approach. The solutions are then stored in csv format. Figure 2 depicts the case study building: a ground-level medium-size office nominally located in Nottingham (UK), featuring a 300 m² space subdivided into five zones (four external and one core zone) with a floor to ceiling height of 2.7m.

Each façade has an operable ribbon window without any internal or external shades. 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.

**Search method and sequential optimization algorithm**

Building optimization problems are most frequently solved using population-based metaheuristic search methods, such as evolutionary and particle swarm algorithms (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. In fact, a set of two different series of experiments have been performed to evaluate the sequential approach, giving 8 combinations of tests: analysis on different initial values and eventual grouping of the design parameters used at the start of the sequential search. The initial values are a low bound, middle range, upper bound and random base points. Each variable can be grouped within the pertaining building element (as displayed in Table 1) or optimized separately (ungrouped). As an example, building shape type, orientation and window-to-wall ratio can be grouped under the “building geometry” category and optimized altogether.

Figure 3 details the algorithm of the sequential optimization approach.

![Figure 3: The sequential optimization algorithm.](image)

It is herein assumed that, as an example, the sequential search is performed adopting a low-bound variables’ value and with parameters grouped within the same element category. The variables analysed in the example are shape type, window-to-wall ratio, fabric type, HVAC system, setpoint and setback temperature setpoints. The sequence begins by identifying all possible combinations of the first two variables under the geometry category (according to their possible design options) which are the shape type and window-to-wall ratio, with all other variables (fabric, HVAC system and controls) fixed at their low-bound basepoint and not considered in the optimization process. In the example, the shape type has 4 possible values, while the window to wall ratio has 3, resulting in a total of 12 (4x3) possible alternatives. A Pareto ranking on the 12 design options results in 2 Pareto-optimal solutions. All other geometry combinations (dominated solutions) have been eliminated from the sequence. The 2 “optima” from the first stage of the sequence are used to constrain the search space of the next stage where the building fabric is explored, and the remaining variables (HVAC system and controls) are kept fixed. Here, the building fabric has 4 possible options and with the two optimal geometries from the first stage (geometry optimization), there are 8 (4x2) possible design options. The Pareto ranking identified 4 solutions from the set of alternatives. Again, these Pareto-optimal solutions will constrain the search space of the HVAC system optimization stage (while the controls are kept fixed). This process is repeated until the last stage (controls optimization) where the final optima are identified.

**Identification and assessment of robust solutions**

A deterministic approach to identify robust Pareto-optimal design solutions and evaluate their robustness has been defined in this research based on the definition that a design solution can be considered robust if it remains Pareto-optimal regardless of the uncertain conditions.
This approach is implemented in a two-stage process described as follows: 1) obtain the optima and sub-optima sets through the Pareto ranking of the design solutions as trade-offs between the evaluated objectives for each combination of the uncertain conditions (4 in this paper), and 2) for each design solution, count the number of uncertain combinations for which the solution is Pareto optimal. A count of 0 indicates regardless of the uncertain conditions, the design solution is always sub-optimal, while if this equals the total number of combinations of uncertain conditions, the robustness of the solution is maximum (100%), as the design remains optimal regardless of the considered boundary conditions. A count equal to any number between 0 and the total number of uncertain conditions determines the degree of robustness of the other optimal solutions (by dividing it to the total number of uncertain combinations). A count equal to 1 in this paper defines a solution robust to only a combination of uncertain condition, therefore being 25% robust, while 2 represents 50% robust, and 3 defines 75% robust.

Results

The results presented in this paper are divided into two sections: analysis of the impact of the uncertain boundary (aleatoric) conditions on the Pareto-optimal solutions; and the identification of robust Pareto-optimal solutions.

Uncertainty performance impact on Pareto-optimal solutions

Figure 4 breaks down the frequency variation of Pareto-optimal design solutions obtained from a full-factorial search (as a benchmark) and from the sequential experimental tests (initial values and eventual grouping of the design parameters used at the start of the sequential search) for the minimization of energy demand and warm discomfort hours for each combination of uncertain boundary conditions varying weather conditions and internal loads.

![Figure 4: Frequency variation of Pareto-optimal solutions benchmarked against a full-factorial search.](image)

In a comparison scenario-by-scenario, 6 out of 8 sequential tests for the TRY weather file and low internal loads scenario (TRY-Low) found the same number of Pareto solutions obtained from a full-factorial search (3), evaluating up to 169 iterations. Instead, on average, 45% of the optima were found for DSY weather file and high internal loads (DSY-High), where the ungrouped optimization of building elements with middle value starting point shows the same frequency of optima found from a full-factorial optimization (5), but with only 61 function evaluations. Both TRY weather file/high internal loads and DSY weather file/low internal loads combinations display an average percentage of optima (67%) compared to a full-factorial search, with the former obtaining the same number of optima across each experimental run (2) and the latter being able to identify the same number of Pareto-optimal solutions as a full-factorial optimization in a grouped search with random initial starting point within 247 function calls.

Robust Pareto-optimal solutions

Figure 5 and 6 illustrate the Pareto sets for each uncertain scenario, respectively for a full-factorial optimization and for the experimental tests of the sequential search. Since the conventional representation of the trade-off between two objectives and the shape of the Pareto front as a continuous line between solution points can be misleading as there is no guarantee that any solutions exist between the solutions found by the search or that the trade-off is smooth (Wright et al., 2013), Pareto fronts are portrayed as attainment curves connecting the sets of Pareto-optimal points represented by coloured dots, dividing the objective space into the region dominated or non-dominated regions. Instead, results from the sequential search indicate that, in 5 out of 8 experimental tests, frequency deviation in number of optimal solutions found is lower for climate scenarios rather than occupant behaviour. Table 4 displays the number of function evaluation across scenarios for the experimental tests of a sequential search as compared to a full-factorial optimization, where the highlighted cells represent the experimental tests that found the same number of Pareto-optimal solutions obtained from a full-factorial optimization.

### Table 4: Comparison of function evaluations.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>TRY</th>
<th>DSY</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>Group</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low</td>
<td>69</td>
<td>95</td>
</tr>
<tr>
<td>Middle</td>
<td>153</td>
<td>95</td>
</tr>
<tr>
<td>Upper</td>
<td>153</td>
<td>95</td>
</tr>
<tr>
<td>Random</td>
<td>169</td>
<td>95</td>
</tr>
<tr>
<td>UNGROUPED</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low</td>
<td>20</td>
<td>29</td>
</tr>
<tr>
<td>Middle</td>
<td>52</td>
<td>34</td>
</tr>
<tr>
<td>Upper</td>
<td>54</td>
<td>31</td>
</tr>
<tr>
<td>Random</td>
<td>52</td>
<td>33</td>
</tr>
</tbody>
</table>

Full factorial: 52488, 52488, 52488, 52488
dominated by a Pareto set. Each colour code indicates whether a particular solution is unique to a single combination of uncertain boundary condition or if has been judged optimal in other combinations. If the latter, then the size of each plotted optima increases to represent its robustness: the largest the coloured dot, the more robust a particular solution.

Figure 5: Pareto fronts for each uncertain scenario and robustness of the solutions (full-factorial optimization).

A general consideration regarding the comparison of the solutions is that, as expected, an increase in internal loads results in a reduction in energy demand but with an increase in warm discomfort hours, with the source of weather file dictating similar trends but impacting the distribution of the solutions. Additionally, a reduction in internal loads results in a wider Pareto front with large differences in trade-offs between optimal solutions.

As portrayed in Figure 4 and 5, and Table 4, a full-factorial approach obtained 17 robust Pareto-optimal solutions across the scenarios, evaluating 209952 function calls (52488 x 4 scenarios). Among these, 7 optima were only found in one scenario, therefore displaying low robustness (25%), with instead 10 optima showing higher robustness percentages: 2 solutions being 50% robust and 2 solutions being 75% robust. None of the solutions are robust across all scenarios (100%).

In comparison, as displayed in Figure 6, the sequential optimization experimental tests with grouped building design elements starting at low (10 optima being found), middle (11), upper (12) and random (13) variable’s values, found the same optimal solutions obtained from a full-factorial search, but with a lower frequency. However, the two solutions 75% robust were always found across the sequential experimental tests and one of the two solutions displaying 50% robustness were obtained in 3 out of 4 experiments. Therefore, only one solution with a medium robustness degree appears to be missing, with all the others being the solutions displaying low robustness (25%).

The behaviour of the sequential tests with ungrouped building design elements shows instead a different pattern. In fact, while the sequential optimization starting at the upper variables’ value displays the same solutions found from a full-factorial search, but with a lower frequency, the sequential tests with low and middle starting point found a different set of optimal solutions, with the sequential search with random initial starting bound displaying a mix between new and previously obtained optima. All the solutions from a low-bound search (10) displayed low robustness (25%) while 12 optima out of 14 obtained from a middle-bound search were found twice across scenarios, therefore showing a 50% robustness. Furthermore, while the ungrouped sequential search starting at the upper bound found the same number of robust optima and degree of robustness as the grouped upper-bound search, the sequential test with random bound obtained 6 solutions out of 12 repeated twice (three 50% robust optima).

Discussion

The combinations of uncertain boundary conditions in both a full-factorial and sequential search drive the frequency of Pareto-optimal solutions being identified. It has been found that a sequential search, across scenarios, identified, on average, 70% of the Pareto-optimal solutions obtained from a full-factorial search, with a computational saving of function evaluations of 99.99%.

As portrayed in Figure 4 and Table 4, in a sequential search, the initial values of the design variables have an impact on the number of optimal solutions identified by each experimental test in a warmer climate with low and high internal loads, otherwise it appears to be insensitive. Additionally, it has been observed in Figure 6 that variables grouping within building element categories affect Pareto optimality. In fact, while the sequential optimization experimental tests with grouped building design elements always displayed the same optimal solutions found from a full-factorial search, the ungrouped search found that 60% of the solutions were not “globally” optimal.

Generally, it appears that the lower frequency of optima found within the grouped sequential searches does not have a significant influence on the ability to obtain solutions displaying medium and high robustness. Instead, it affects the frequency of low-robust solutions being found. Additionally, the results appear to be homogeneous across tests in terms of optimality and robustness, with only small deviations.

A similar pattern cannot be identified for the ungrouped sequential experiments since there is a significant discontinuity across experimental tests in terms of optimality of the solutions and their robustness. However, it is noticeable that, across all the experiments, only solutions with medium robustness were identified. It is particularly interesting that a middle-bound search found more solutions with 50% robustness degree (6) than a full-factorial search (3). None of these solutions were found during a full-factorial search and therefore cannot be considered “globally” optimal, however they all show performance metrics very “close” to the “global” optima.

In a comparison scenario-by-scenario, 6 out of 8 sequential tests for the TRY weather file and low internal loads scenario, the ungrouped optimization of building elements with middle value starting point for DSY weather file and high internal loads and the grouped search with random initial starting point for DSY weather
file and low internal loads identified the same number of optimal solutions obtained during a full-factorial search. Although decision-making is out of the scope of this contribution, in lieu of the obtained results, building stakeholders might want to prioritise a smaller search space over a higher frequency of Pareto-optimal solution, mostly compromising solutions that display a low degree of robustness across scenarios. Additionally, it might be more desirable to prioritise a higher frequency of Pareto-optimal solutions with a medium robustness degree and associated computation savings rather than a lower number of optima with higher robustness at an additional computational cost.

**Conclusion**

This contribution evaluated the reliability (robustness) of a sequential whole-building design optimization approach, benchmarked against a full-factorial search, to determine the optimal selection of building geometry, fabric, energy system and its controls. In this research, a non-probabilistic method based on uncertain scenarios related to occupant behaviour and weather conditions is adopted to identify robust Pareto-optimal solutions that
minimise energy demand and warm discomfort hours. It has been found that a sequential search, across scenarios, identified, on average, 70% of the Pareto-optimal solutions obtained from a full-factorial search, with a computational saving of function evaluations of 99.99%. Additionally, it appears that the ability to obtain solutions displaying medium and high robustness is not affected by the lower frequency of optima found across scenarios, only affecting the frequency of low-robust solutions being found. This research showed the potential of a sequential search based on a four-stage approach, in contrast with previous findings from literature that discarded a sequential process in favour of a simultaneous approach. Further research is needed to validate the findings and gain additional understanding on the effectiveness and reliability of the sequential approach by increasing the granularity of the problem formulation, which represents a limitation of this study. Further improvements of the algorithm behind the sequential search will focus on the ability to identify the remaining optimal solutions. Additionally, benchmarking the sequential search against a genetic algorithm will offer insights on the efficiency through an in-depth study of the computation performances. Additional analyses on the effect of uncertainty performance on Pareto optimality & robustness of the solutions and its correlation between the impact of different starting point and variables’ grouping are needed, focusing on the variation in the design solutions throughout the optimal solutions set to draw insights on the variables driving the trade-offs.

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**References**


