Integrated Building Performance Optimisation: Coupling Parametric Thermal Simulation Optimisation and Generative Spatial Design Programming

Yair Schwartz, Rokia Raslan, Ivan Korolija, Dejan Mumovic
IEDE - Institute for Environmental Design and Engineering
UCL, London, United Kingdom

Abstract

The evaluation of building performance is currently implemented through the modelling and simulation of buildings, where often a single model is built and assessed based on user-generated building design inputs. Although recently developed parametric design and optimisation applications enable researchers and practitioners to automate the iteration and evaluation of building design alternatives, the integration of automatic spatial arrangement generators into the framework of these applications is still very limited.

This study aims to examine the potential coupling of parametric thermal simulations and optimisations with automated generative spatial design programming, in order to incorporate different spatial arrangements as an independent simulation parameter. For this, a generative spatial arrangement algorithm was developed, and a parametric optimisation analysis was carried out.

Results show that the proposed algorithm successfully automated the generation of numerous floor layouts, and the optimisation has identified a series of optimal design alternatives. This method can help decision makers to explore a significantly wider range of possible design solutions, and offer design teams optimal designs.

Introduction and Aims

Building thermal simulation tools are commonly used for the evaluation of building performance and compliance requirements (Nguyen et al. 2014, Raslan & Davies 2010). Currently available simulation tools enable the analysis of building thermal performance through a relatively simple modelling process that largely involves a single model that is built and assessed solely based on user-generated building design inputs. Thermal simulation analysis is, therefore, by nature often limited to examining specific and rather limited aspects of buildings properties.

In more extensive analysis studies, model properties (also denoted as 'parameters') are modified and updated in an iterative manner, new models are created – often hundreds or thousands (Naboni et al. 2013) – and their performance is evaluated (Figure 1). Parametric thermal simulation is often used for exploring different design alternatives and finding the optimal combination of parameters that leads to the design with the best performance (Zhang 2009; Panczak & Cullimore 2000). Through the use of

parametric thermal simulations, optimal solutions can be found using various strategies, e.g.: brute force, sensitivity analysis or optimisation methods (Paoletti et al. 2011).

While the outputs of parametric thermal simulations can provide useful design evaluation feedback, the implementation of an analysis where the designer is able to examine a range of spatial design alternatives is challenging, due to the potential complexity of the modelling process and the time it takes to manually iterate it (Calleja Rodríguez et al. 2013; Nguyen et al. 2014).

Recent computational developments, however, have resulted in new automated parametric design optimisation tools, such as jEPlus, Galapagos-Grasshopper and various BIM applications (Bahar et al. 2013; Chatzikonstantinou 2014; Zhang 2009). By using these applications, researchers and practitioners can now automate the iteration, evaluation and selection of thermal models and building design alternatives to support the implementation of parametric thermal simulations and optimisation analysis.

Whereas new computational applications enable a quicker and more efficient analysis process, only simple, none-geometric building properties (e.g. U-Values, building orientation, loads etc.) can typically be amended between runs. In addition, while some tools enable the modification of very basic geometric building properties such as windows, overhangs or louvre dimensions, or very simple room dimension modification, the alteration of spatial arrangements or layout for this purpose is still
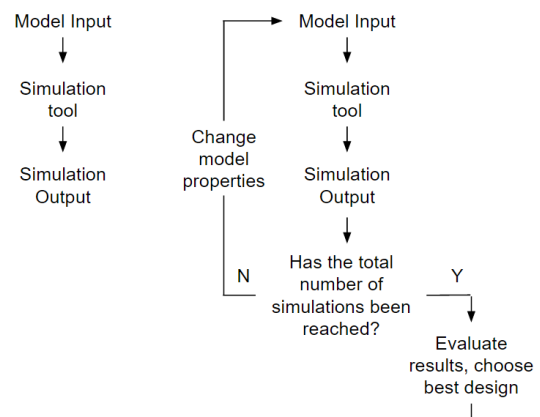

Figure 1: a) A simple input-output thermal modelling and simulation stream. b) Iterative modelling, modification simulation and evaluation stream.

very limited. This is due to the fact that these are regarded as more difficult properties to control, and involve a relatively complex operation for simple parametric tools. As such, the integration of automated generative design programming into thermal simulations to evaluate the performance of a range of building layouts and spatial arrangements can address this limitation and consequently provide a powerful decision-making support tool.

This paper aims to examine the potential coupling of parametric thermal simulations and optimisation with automated generative spatial design programming, in order to incorporate different spatial arrangements as a new and independent simulation parameter.

Its main objectives are:

- To test an algorithm for generating spatial arrangements and building designs.

- To test the coupling of the generated spatial arrangements, in the form of .idf files (EnergyPlus Input Data Files), with parametric thermal simulations and optimisation tools (jEPlus and jEPlus+EA).

Background

Parametric Thermal Simulations

Figure 2, (adapted from Zhang, 2012), shows the three steps for carrying out parametric thermal simulation analysis:

A. *Scenario set-up:* A description of the different input parameters. In the example shown in Figure 2, each design category (U-Value, WWR and heating system) has numerous possible input parameters. The overall number of possible combinations of input parameters is called the model Search Space.

B. *Model generation and Simulation*: Once the input parameters and search space are defined and created, a model parameter controller iteratively generates individual models, based on the combinations defined in step A. These models are then simulated, using a thermal simulation tool.

C. *Evaluation:* Lastly, simulation results are stored and their thermal performance is evaluated.

Zhang (2012) notes that while many building design optimisation studies have been carried out in recent years, most researchers have traditionally preferred developing their own parametric controller and optimisation tools, because the nature of building optimisation problems tends to vary greatly across different buildings. Most self-developed-tools were never made public and they are not available for others to use.

Once a parametric simulation is set up, an optimal design can be simply found by simulating each and every model in the search space (known as Brute Force approach), or by performing a sensitivity analysis – modifying one simulation input parameter at a time and examining its impact on the overall building performance. These methods have been used extensively in the past for finding optimal building designs aiming to maximize their
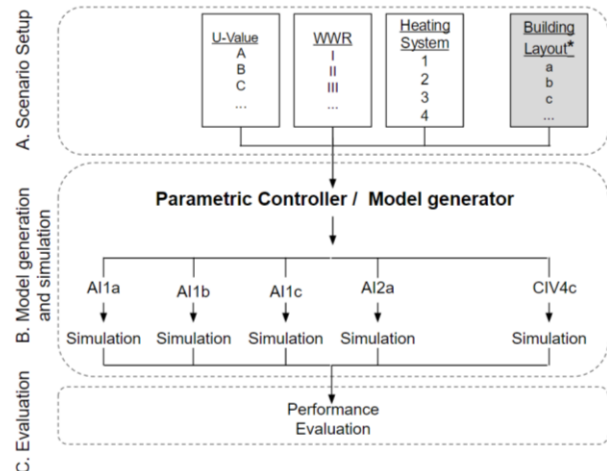

Figure 2: The steps of a Parametric Thermal Simulation

thermal performance (Anton & Tănase 2016; Aste et al. 2015; Hopfe & Hensen 2011; Asl et al. 2014).

Coupling Thermal Simulations with Optimisation

However, as this approach is time and resource consuming (Calleja Rodríguez et al. 2013; Nguyen et al. 2014), studies with a larger search space often use advanced optimisation algorithms. Optimisation, in this mathematical sense, is the process of searching for the best, or near best, available solution out of the whole search space, without having to examine each and every individual solution (Programming 2014).

Consequently, a wider range of studies are using parametric simulation tools coupled with optimisation algorithms such Genetic Algorithms (Nguyen et al. 2014). This includes studies where optimisation algorithms were used for minimising overall loads, annual energy consumption, life cycle performance and other performance-related criteria (Congradac & Kulic 2009; Camp et al. 1998; Wang et al. 2014; Basbagill et al. 2014).

While optimisation algorithms have proven to be powerful, most parametric controllers used in optimisation studies allow only very basic examinations of the geometric properties of buildings. This includes properties such as window-to-wall ratio, floor contour or minimal geometric alterations to thermal zones.

Wang et al. (2015) used parametric simulation to examine the impact of building shape on the indoor thermal comfort in green residential buildings in China. The building shape, however, was only represented as the ratio between the building surface area to its volume. In another study, (Geletka & Sedláková, 2011) conducted a parametric analysis to examine how building geometries can affect energy consumption. However the 'shape' parameter in the study could only be randomly picked out of a series of pre-designed basic building shapes. Tuhus-Dubrow & Krarti (2010) enabled a parametric manipulation of pre-designed basic buildings contours (rectangle, L-shape, T-shape, H-shape and others), to examine their impact on overall performance.

No application has of yet enabled a true parametric evaluation of building geometry and spatial arrangement on building performance using thermal simulation tools.

Layout Generation

As automatic spatial design requires extensive computing resources, only a few studies have addressed it as a parametric proces. Of those, the following two strategies can be defined:

A. *Simple Building Shape Generation: a "Top - Down" Approach:*

Most studies that used automatic shape generators, applied simple geometric manipulations to buildings shapes, as described in Figure 3 (Basbagill et al. 2014, Bichiou & Krarti, 2011, AlAnzi et.al 2009, Tuhus-Dubrow & Krarti 2010). In these studies, whole floors were considered to be empty 'shells' – single thermal zone – where only their perimeter and footprint could be modified, while maintaining the same overall floor area. An interesting 'top-down' approach that does take internal partitions into account, was presented by Duarte (2001), who generated social houses in Portugal by using shape grammars. This computational process generates a geometric shape by applying a series of geometric rules to a basic shape. Through the application of this method, the study showed how a given plot could be sub-divided numerous times following pre-defined rules, to form a building layout. While this approach did result in the generation of what can be considered sensible buildings, it is only useful for the generation of relatively simple building layouts.
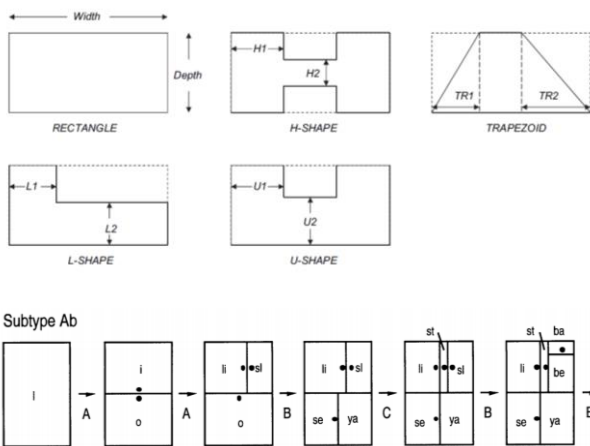

Figure 3: Above - Contour manipulation (Tuhus-Dubrow & Krarti, 2010). Bottom - Shape grammar and sub-division of pre-defines spaces (Duarte 2001).

B. Complex Building Geometry Generation: a "Bottom – Up" Approach

Other studies have attempted to generate building designs by manipulating and joining individual spaces. Caldas (2008) applied a geometric manipulation to generate different design alternatives for a small museum building. This was undertaken by defining a basic layout of four equally-sized adjacent spaces, and changing their width

and length parameters. Despite the strict initial starting point (Figure 4), this method resulted in a relatively large variation of different shaped buildings. Another building generator method was presented by Chatzikonstantinou (2014), who applied shape grammar-type algorithm on rooms ("bottom-up") rather than on a plot ("top-down). The study, however, resulted in basic building shapes and some spaces with unrealistic dimensions
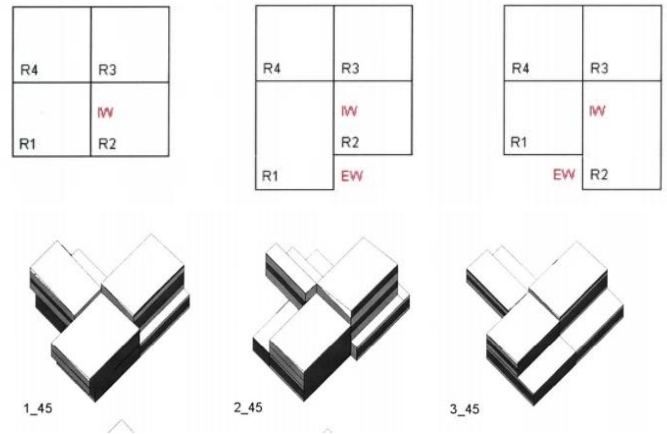

Figure 4: The basic starting-point layout in Caldas (2001)*, and some of its parametric variations*

To summarize, this review concluded that:

- The computational developments of the recent years, in the form of parametric thermal simulations and optimisation methods, have a great potential for carrying a large number of thermal simulations very quickly. This can enable a true examination of various design scenarios and inform design teams with the optimal design.

- Spatial arrangements have still yet to be truly incorporated in thermal optimisation studies.

- Previous spatial arrangement algorithms have resulted with limited outcomes – algorithms for realistic design scenarios still lack.

Proposed Method

The design of this study is a combination of several steps, as shown in Figure 5:

A. Defining a building border envelope. The envelope represents the volume in which the building can be built.

B. Setting the optimisation scope (parameters taking part in the optimisation process).

C. Carrying the optimisation process. This iterative process is broken down into two sub-processes – generating new designs and simulating and evaluating results.

D. Finding the optimal design.

Figure 6 further illustrates the tools used in the optimisation process (i.e., the abovementioned stage C). These include:

C.1. The generation of building geometries and idf files.
C.2. The utilisation of the optimisation kit.
C.3. Result evaluation.

To undertake the parametric simulation and the optimisation, the following tools were used:

- EnergyPlus was used for the thermal simulations.

- jEPlus – a simple EnergyPlus user interface that controls parametric simulations within the EnergyPlus simulation environment – was used as the parametric controller.

- jEPlus+EA – an interface that allows the integration of the Non Sorting Genetic Algorithm (NSGA-II) to jEPlus.

To test the proposed method, an algorithm for generating building floor plans was developed, based on some principles from the studies outlined in the aforementioned studies.

While EnergyPlus is regarded as one of the most reliable thermal simulation tools, and while jEPlus and jEPlus+EA have been tested and validated in various studies (Zhang, 2009, Zhang 2012), the 'proof of concept' execution and the validation of the proposed approach included two examinations: The first – aimed to examine the implementation of the automatic layout generator algorithm for a simple spatial division task. The second aimed to couple the spatial design algorithm outputs with jEPlus+EA.
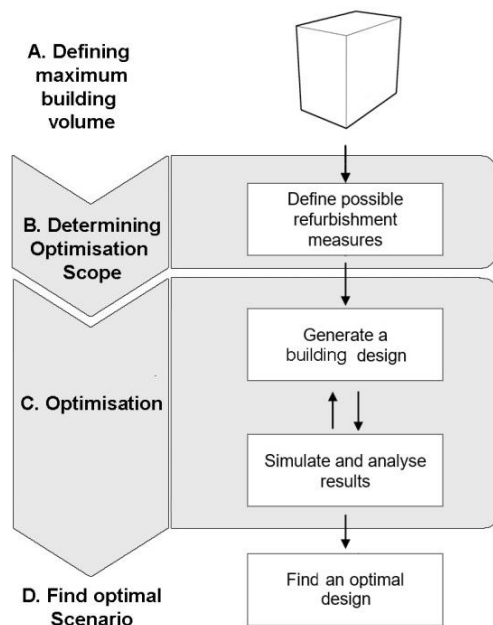

Figure 5: Proposed method – starting with the plot volume, followed by design generation and evaluation, ad results in the final optimal design.

Figure 6: Tools used in the optimisation process (Stage C in Figure 5): jEPlus, jEPlus+EA, EnergyPlus

Generative Design Principles

To enable the automatic generation of building layouts, a new generative spatial design algorithm 'PLUTO' (Parametric LayoUT generatOr) was developed.

PLUTO is a computer software that offers designers, at an early stage of design, multiple layouts, based on a set of design inputs and restrictions, given by the designers.

PLUTO can potentially cover each and every design solution to a given input and restriction scenario. This means that a design that would have been achieved by a designer without the code can be found by using PLUTO. This process can save time by achieving similar designs to that of a human designer. It can also, however, offer new designs that meet the same spatial criteria – but were never fully developed or thought of by the designer. These designs can then participate in an optimisation process, to find which one has the best environmental performance.

PLUTO's operation is based on the following steps:

a. The user is asked to identify the design problem – describe the plot area, number of stories, number of rooms, room functionality etc.
b. Points are distributed across the given plot. Each point represents a room, and will, at the end of the spatial arrangement process, be surrounded by four walls.
c. A series of checks and rules are applied for each point, based on the designer`s input, e.g.: ensuring the width and length of each room are within a pre-defined dimension range, making sure a room proximity matrix is followed etc.
d. External and internal walls are detected.
e. Windows are added to external walls, following a user-defined window-schedule input.

Execution

Case 1: Simple Space Division

The aim of the first test was to examine the robustness of PLUTO by testing its ability to find all possible spatial arrangements of a given design task.

To enable this, a simple spatial arrangement task (Figure 7) was designed, where a set of three rooms with fixed dimensions should be placed on a plot sized 720 x 720 cm. For this particular design task, when the orientation of the model is fixed, there are only four possible solutions, as described in Figure 8.

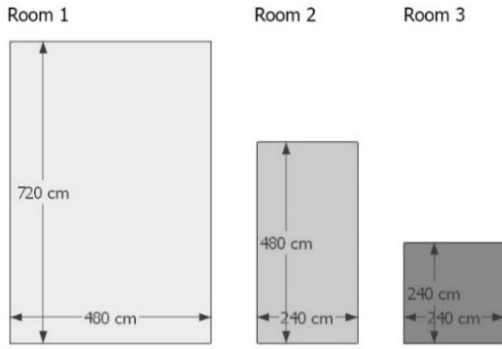It took an average of 21.4 seconds for the code to find all four possible arrangements (overall 10 runs).
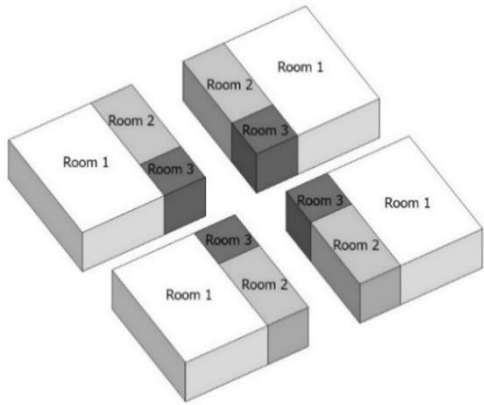
Figure 7: Case 1-The three rooms and their dimensions

Figure 8: The four possible spatial arrangements for Case 1.

Case 2: Terrace House

For the second test, a single-family terrace house building was generated and its performance optimised.

As the generated geometries should aim to represent a terrace house, spatial characters and properties of terrace houses (such as the plot size, number of floors and rooms, possible rooms dimension etc.) had to firstly be identified.

Based on work undertaken by Oikonomou et al. (2012), that identified typical dwellings in London, a typical terrace house was determined.
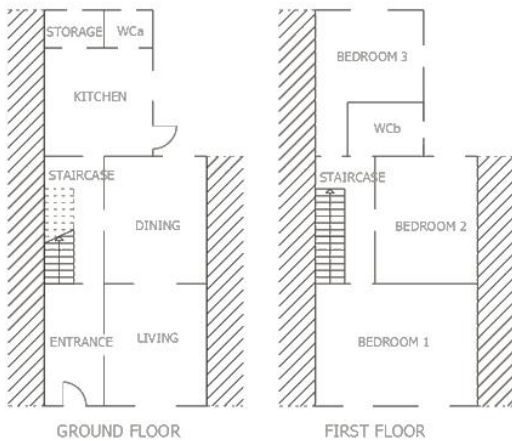

Figure 9: A 'typical' London terrace house (Oikonomou et al., 2012)

Based on an original building layout (Figure 9), the dimensions of the plot for the new two-story generated building was set to be 6.0 x14.6 meters. For the purpose of the floorplan generation, some spatial input variables were slightly modified or merged for simplification purposes.

The range of allowed room dimensions, which is one of the main algorithm input parameters, is shown in Table 1. The wall-to-ceiling height was set to 3.0 meters, and an adjacency matrix that describes the relationships between the different rooms was also defined. As the code was designed to identify external walls that touch the edge of the plot, these were defined as adiabatic surfaces that had no windows.

		Width		Length	
		Min	Max	Min	Max
Ground	Living	540	600	360	440
	Dining	360	440	360	440
	Kitchen	360	440	360	440
	Core (stairs)	160	240	360	440
1st floor	Bedroom 1	540	600	360	440
	Bedroom 2	360	440	360	440
	Bedroom 3	360	440	360	440
	Core (stairs)	160	240	360	440

Table 1: Allowed room dimension range

The optimisation scenario described in this section included only geometric-related building properties: spatial arrangements and window-to-wall ratio per each room individually. Each window had its own particular ID reference so its size could be examined independently of any other window (e.g., the size of the living room southern window could be modified and evaluated independently of the kitchen windows). All other model inputs were identical – envelope build-ups and materials, rooms schedule, rooms thermostats, occupancy times etc.

An overall 15 spatial arrangements were generated (Figure 10) and tested. Each model consisted of 8 thermal zones. Each thermal zone was allowed to have a maximum of two windows, with a window-to-wall ration of either 25 or 75%. Given these conditions, the search space had an overall 983,040 possible geometric combinations.

As a main objective of this study was to test the robustness of the proposed method, the selected optimisation objectives were defined as annual district heating and annual district cooling consumption. As the outcome of an optimisation for these objectives can be roughly predicted, it allowed an objective evaluation of the success of the optimisation process by comparing the outputs with the anticipated results.
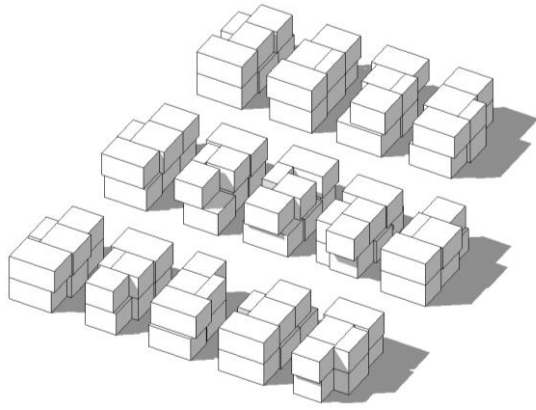
Figure 10: The 15 building geometries generated by PLUTO.

Figure 11a. shows that a pareto-optimal front with 3 optimal models was found. Figure 11b shows the two spatial arrangements with the best performance (black dots) versus the two arrangements with the worst performance (red dots). It is evident that some geometries performed better than others.

All best-performing models had a minimal window-to-wall ratio (25%). This was expected, as the optimisation objectives were energy consumption, which is related to heat loss through the buildings envelope. Similarly, spatial arrangements that had a lower surface area to volume ratio (or, more compact buildings) – resulted with better performance. This is, again, because heat in building is lost through their external envelope.

Table2 shows the external surface area to volume ratio of the best and worst spatial arrangements from Figure 11b.
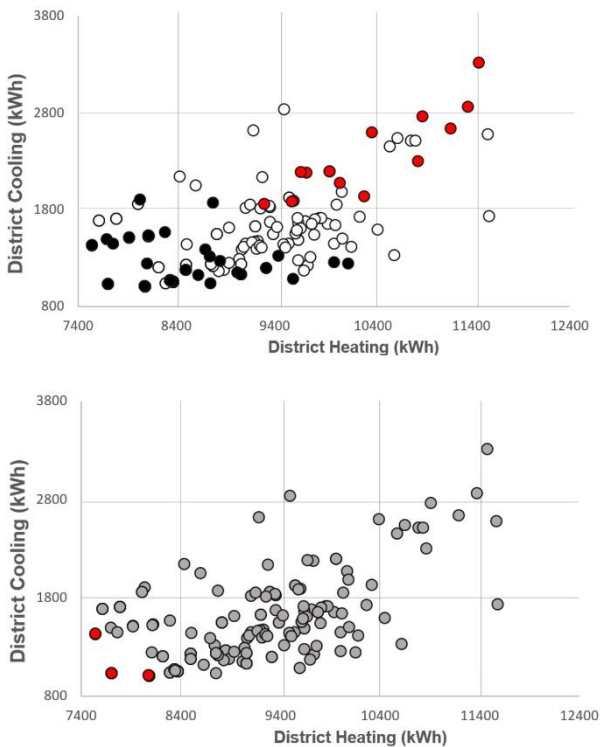

Figure 11: a) Pareto-optimal front of 3 optimal models. b) The performance of the best and worst models

Conclusion

This study examined the potential coupling of computational generative design algorithm with parametric simulation and Genetic Algorithm optimisation.

Addressing the gaps as they were described in the paper, results highlighted that the proposed generative design algorithm successfully managed to find numerous building design alternatives. The study has also illustrated how spatial arrangements can potentially be integrated into the parametric analysis framework and GA optimisation toolkit, and presented a series of pareto-optimal models that were found. In comparing the surface-to-volume ratio of the best-performing models with the worst ones, the former had a favourable performance.

This method can help decision makers to explore a wide range of possible design solutions, and offer design teams an optimally efficient design.

The outcome of this study is a set of early-stage results that show that the proposed methodology and workflow can work. Future work will aim to further implement this method to help answer more complex optimisation problems, such as assessing the impact of geometrical arrangements on conflicting objective functions (energy performance and daylight factor), or determining the more 'favourable' solution when examining the option of either refurbishing or replacing existing buildings.
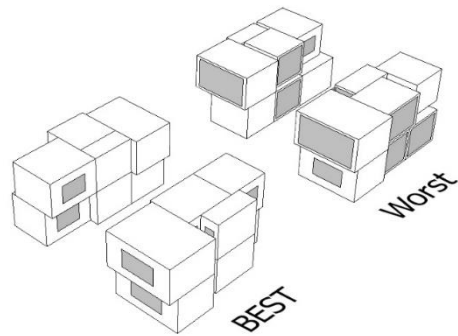

Figure 12: Best and worst performing geometries

	Model number	Overall external surface to Volume Ratio	Non-Adiabatic external surfaces to Volume Ratio
Best	10	0.985	0.886
	12	1.024	0.819
	1	1.059	0.795
Worst	6	1.077	0.937
	11	1.077	0.983
	8	1.016	0.95

Table 2: Best and worst geometries surface area to volume ratio

Acknowledgement

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