A Three-Part Visualisation Framework to Navigate Complex Multi-Objective (>3) Building Performance Optimisation Design Space

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Abstract
This paper describes a visualisation framework for organising data outputs generated from a complex multi-objective optimisation design space. The three-part visualisation framework is structured to identify solution clusters along the Pareto front, before providing designers with design space navigation control through genotype value displays. These provide smaller focus design spaces which are then supported by spatial displays of a series of solution phenotypes and their respective performance simulations. This visualisation tool aims to provide a diverse range of quantitatively high-performance design solutions determined through building performance simulations, that can further subsequent higher order qualitative design evaluation such as design aesthetics.

Introduction
In its simplest case, building performance simulation (BPS) constitutes digital representations of actual building physics which are tested on a case-by-case basis where a human designer manually assesses the computer results and constructs a subsequent improved design iteration to be tested anew. This tedious method investigates a small sample of the potential design space. Building performance optimisation (BPO) on the other hand, is a goal-oriented process where a design space is defined by building parameters and specific goals are input into a computer-controlled process (Brown and Mueller, 2016). The computer then automatically searches the design space for the best performing results, which are communicated back to the human designer. BPO when applied to a single goal, such as minimising energy use, is simple and results in a single conclusively optimal design; however, once multiple objectives are present, the optimum is ambiguous and involves navigating trade-offs between different performance criteria and subjective qualities of the design.

This paper addresses two typical problematic trade-offs in multi-objective BPO that are inherent to the setup and evaluation of an optimisation process (1) Model parameters are designed by a human actor and therefore still limit the design space explored; and, (2) When the number of resultant objectives being optimised are greater than two, trade-offs, data presentation and therefore the decision-making process are difficult to clearly present to a user. In addition, such presentation typically obscures the qualitative aspects of a building design key to making a reasonable design choice (Heusser et al., 2018). Both issues are discussed in detail and solutions are proposed by the authors. The results are applied to the design problem of a large housing development in Singapore.

Background
Human computer interaction (HCI)
There has been a recent shift towards data-informed architectural design processes, as seen in worldwide adoption of building information modelling (BIM). A building can be visualised as data and additional information like daylighting results can be imported and visualised as false colour maps to study design performance. Compared to traditional approaches, BPS is more readily incorporated into modern workflows, increasing awareness and appreciation towards quantitative building data (Brown and Mueller, 2017). The success of BPO as a design tool that can explore large design spaces, hinges upon data communication (Vierlinger, 2013). This paper focuses on HCI during optimisation; proposing a data framework for BPO results, followed by a visualisation tool that allows the navigation of complex design spaces with multiple performance objectives.

It is easy to quantify data based on clear sets of criteria, like minimum daylight hours or minimum air change rate. However, in architectural design, Bittermann (2009) acknowledged that there exist softer sets of criteria, like building aesthetics, which are difficult to translate into a numeric evaluation. The goal of a BPO design tool is thus, to not only identify solutions with the best objective fitness values but also to empower designers with design space navigation capabilities—presenting the subjective qualities of a design alongside the objective. By enabling both design search and design space navigation, design decisions can then be better informed by quantifiable and “soft” criteria.

Parametric model constraints
Parametric models are generated by model constraints that should be designed to expand exploratory design space in a beneficial manner. Beulow (2012) describes how a set-up with poor genotype or objective values could lead to impractical solutions, albeit ones that still possess high performance. On the other hand, Wang et al. (2006) provides an exhaustive list of constraints, resulting in highly practical solutions which were also uniform in
spatial constructs. One reason for Wang’s constraints was his concern about epistasis—genotype relationship which increases difficulty of locating an optimum, and isomorphism—identical phenotype generated by different genotype combinations, which can skew a design search direction. Since BPO is conducted absent of direct human control, it is important to set-up parametric models which do not suggest highly similar phenotypes.

In traditional BPS workflows, the HCI is represented by a single output which describes building performance in the spatio-temporal domain. Spatially, this comes in the form of daylight renderings, CFD section cuts, daylight analysis grids, or building surface false colour images. Temporally, data may be communicated as timseries charts. Sometimes hybrid approaches are constructed, such as Thermal Comfort Autonomy (Jakubiec, et al. 2017) or Daylight Autonomy (Reinhart and Wienold, 2011). Changes to the original design can then be made to improve on each individual simulation result. However, with BPO, parametric models are constructed to allow computers to handle the process of iterative improvements and evaluations of the results must be programmed into the computer algorithm. For successful design space exploration, the trade-off between parametric model constraints and maximising explorable design space must be addressed. Design considerations must also be successfully translated into computational language such that each genotype combination represents a unique set of results.

Visualising BPO design space

BPO is a design black box and creating an adequate design space requires a complex and potentially sprawling genotype. The data communicated by the computer comes in the form of phenotype displays and objective value documentation. Emami et al. (2000) used a base hexagon to produce a series of diverse yet complex façade designs, before performing structural and daylight simulations. They then moved on to a qualitative discussion on results, arriving at a design after analysing optimal trade-offs along the Pareto front. Marsault (2013) also demonstrated how BPO can provide a spread of environmentally-friendly building design options. To facilitate data communication, both authors provide a visualisation of phenotypes along the Pareto front, coupled with simple indicators of simulation performance results. Buelow (2012) used a similar visualisation through his ParaGen tool, which allows a designer to evaluate each design option quantitatively and qualitatively. Caldas and Norford (2003) provided a different visualisation method by mapping Pareto front phenotypes onto their positions within a scatter plot of objective values—essentially displaying the aesthetics of the optimal Pareto trade-offs in their design space. All 4 authors show that high performance Pareto front design options are diverse in terms of their phenotype, which further illustrates the importance of data communication from the computed results to a designer, as subsequent design decisions are based upon visualised forms.

When describing a BPO generated design space, visualisation tools should identify phenotypes, genotypes and objective values. Buelow (2012) prioritised phenotype comparison, using genotype and objective values to filter design solutions. Kocabay et al. (2017) and Marsault (2013) adopt similar visualisations to display selected solutions of their respective mixed-use projects. This visualisation method is the most commonly adopted, and a designer is allowed design space navigation through filtering of objective or genotype values, with limited understanding of the generated design space.

Vierlinger et al. (2013) and Liuti et al. (2013) attempt to display individual objective value space by plotting fitness values against genotype values. Liuti then combines both objective values into a single function that describes the generated design space. This helps with understanding how genotype combinations affect a solution’s performance. However, the display becomes less effective when genotype number or objectives increase, and a single function becomes difficult to craft. The authors propose that communication of multi-objective BPO results need to meet the following goals: a) To provide a designer with design space visualisation, namely the relative performance of a solution across multiple objectives. b) To communicate genotype values used during BPO, facilitating design space navigation. c) To provide a spatio-temporal visualisation of filtered phenotypes, supporting qualitative and quantitative design decisions.

Methodology

An urban scale mixed-used development in Singapore was analysed using multi-objective BPO. Located next to a busy transportation hub, the site has the potential to connect the hub to surrounding residential and commercial developments. These represent qualitative considerations that could be used to select designs from objectively well-performing results.

The parametric model was set up to test for an amalgamation of spatial conditions such as towers, overhangs and terraces. To maximise exploratable space, design constraints are minimal (Killian, 2006). These include basic quantitative constraints, like site volume and floor-to-floor height, as well as geometrical constraints, like minimum distance between points and minimum polygon angle. These open-ended constraints generate forms with unexpected spatial constructs, independent of traditional model-space constraints. Each design option will be recorded and made identifiable by its various objective values, genotype combination and phenotype rendering. Figure 1 shows a diagram of the proposed optimisation framework, showing how an open-ended design space can be constructed and how the various aspects of the design space can be studied with a three-part visualisation toolbox. Evaluation of Pareto front results returns to an initial query on the best combination of spatial functions.

With an open-ended parametric model, performance outputs become the main BPO driver. This study consists
of 4 outputs which can be divided into 2 groups of 2, with each pair evaluating the building envelope and interior floorplates respectively.

Building envelope design objectives
The building envelope is evaluated by a solar radiation cost function and a wind score fitness function. Both are cumulative area weighted totals across the façade.

Solar radiation simulation is performed using DIVA (Jakubiec and Reinhart, 2011), arriving at an area weighted cumulative total. Wind score of a single wall is calculated based on annual wind direction and wind speed. If an instantaneous wind speed is above 3m/s, a wall which is perpendicular to the wind direction scores better as it helps to divert strong wind. When wind speed is below 3m/s, a wall parallel to wind direction scores better as there is a higher possibility of it channelling wind further downstream. By comparing all exterior façade orientations against hourly annual wind data, an area weighted cumulative total is derived. In short, while a solar radiation minimized building is oriented away from the sun, wind score maximised designs try to orient their envelopes to encourage moderate ventilation rates through urban spaces.

Interior floorplate design objectives
Similarly, the interior floorplates are evaluated by an annual sunshine exposure (ASE, IESNA 2012) (number of hours, with lux levels from direct sunlight only, above 1,000 lx) cost function and a useful daylight illuminance (UDI, Mardaljevic et al., 2012) (% occupied hours with daylight levels within 300-3,000lx) fitness function. DIVA was used for both daylight simulations and both results are generated from 1 simulation process. The UDI fitness value is an area weighted average whereas ASE is a cumulative area weighted sum of hours. UDI helps to filter out designs which have deep floorplates or insufficient allowance between adjacent towers, while ASE helps to maintain a balance between overexposed zones and having useful daylight.

Maximising limited design spaces
Functional constraints
Parametric model constraints were studied and refined into 4 main categories as seen in Figure 1. The main design problem centres around functional constraints. For this test case, spatial functions such as terraces and overhangs were to be tested in configurations of slab block, tower block, courtyard scheme, etc. Each spatial function possesses different characteristics based on its location within the site. Terraces which are found near the middle of the site could hold more private spaces like playgrounds. Based on sun path data, presence of a tower could help provide shade for the rest of the site. On the other hand, short but wider slab blocks could create a built area which has a more even spread of incident solar radiation.

Therefore, rather than designing a model that would always meet spatial constraints in a benign manner, the parametric model was designed to support a wide range of various spatial combinations which are generated based on a wide range of parameters, before being checked for gross floor area (GFA) compliance. These would then undergo BPO to identify solutions with high quantitative performance which will then be evaluated by a human for qualitative performance.

Geometrical constraints
To achieve spatial function flexibility, 4 layers of Voronoi cells were used to generate the massing. Voronoi cells are

**Figure 1: BPO framework**
cell partitions of a plane such that any point located within the cell is the closest to the generating point. This property ensures that no two cells overlap and that adjacent cells share a common boundary. Distance between adjacent layers is 1 module in height, consisting of 5 floors, each 3.3m tall. Voronoi cells are generated from parametric points which can translate along their horizontal plane. Spatial genotype values are represented by \((x, y, z, h)\), where \(x\), \(y\) and \(z\) represent its parametric point position and \(h\) represents the height of the cell. \(x\) and \(y\) are allowed up to \(±2m\) of translation which results in manageable amounts of cantilever as well as a control over cell size. \(z\) is a constant for each point and \(h\) has a range of 0 level to 20 levels, representing each cell’s floor level count. A value of 0 means that the cell is open ground.

**Table 1: Genotype structure**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Cell n</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>(X) (point)</td>
<td>([-2+x_n, x_n+2])</td>
<td>Up to 2m translation</td>
</tr>
<tr>
<td>(Y) (point)</td>
<td>([-2+y_n, y_n+2])</td>
<td></td>
</tr>
<tr>
<td>(Z) (point)</td>
<td>(z_o)</td>
<td>Constant</td>
</tr>
<tr>
<td>Height</td>
<td>([0,20])</td>
<td>No of Floor Levels</td>
</tr>
</tbody>
</table>

Although each cell only has three variables, they combine to produce a multitude of spatial constructs due to the union of different Voronoi cells.

**Topological constraints**

In this test case, the site is populated with 40 points which leads to 40 Voronoi cells. Across a total of 4 floor levels, total cell and point count comes up to 160. Since each point is allowed up to \(±2m\) of horizontal translation, and can also be open or enclosed, a shifting effect is created, and solutions are tested which can be similar in the general build but with qualitative and quantitative performance differences due to the shifting of modules.

**Quantitative constraints**

With a large solution space, it was important to only perform BPO for models that come within 1% of a target GFA. Together with site boundary and fixed floor-to-floor height, quantitative constraints ensure that solutions within a design space are compared based on the same conditions. These constraints serve as a precursor for fitness evaluation before lengthy environmental performance simulations are used.

**Visualisation of multi objective datasets**

As noted in the introduction, with the rapidly increasing use of simulation tools and evaluation techniques, a BPO design search should start to incorporate design objectives beyond the purely objective. This in turn increases the complexity of data interpretation and a clear data classification framework is required to support design decision making.

**Part 1: Display of N-dimensional objective values of design optimisation space**

One of the strengths of selecting a multi-objective approach is to allow genetic algorithms to consider performance across multiple objectives at the same time. A display of such a complex space should also reflect similar considerations.

In this test case, there are 4 objectives: min. solar radiation, max. wind score, max. UDI and min. ASE. For effective comparison, each objective value would firstly be normalised based on their respective maximum and minimum values. For intuitive understanding, Table 2 shows how the normalised range of \([0,1]\) should all have the upper limit representing the desired objective value.

**Table 2: Normalised objective values and their respective axis**

<table>
<thead>
<tr>
<th>Objectives</th>
<th>Normalised Range</th>
<th>Axis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Solar Radiation</td>
<td>Max</td>
<td>Min</td>
</tr>
<tr>
<td>Wind Score</td>
<td>Min</td>
<td>Max</td>
</tr>
<tr>
<td>UDI</td>
<td>Min</td>
<td>Max</td>
</tr>
<tr>
<td>ASE</td>
<td>Max</td>
<td>Min</td>
</tr>
</tbody>
</table>

Using a 3-dimensional plot, the X, Y and Z axes are assigned to solar radiation, wind score and UDI respectively. Based on each solution’s performance across these 3 objectives, they are plotted as points within a 3-dimensional plot. Points are then coloured based on their ASE performance.

In a multi-objective design space, each solution can only be non-dominated or dominated. Non-dominated solutions are deemed to have the best performance as no one objective can be further improved without sacrificing other objectives. Conversely, dominated points are those where better solutions on the Pareto optimal 4-dimensional surface exist. Each solution can be represented by a data tree branch as seen in Table 3.

**Table 3: Data tree structure**

<table>
<thead>
<tr>
<th>Solution no.</th>
<th>Solar Radiation</th>
<th>Wind Score</th>
<th>UDI</th>
<th>ASE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.85</td>
<td>0.32</td>
<td>0.48</td>
<td>0.97</td>
</tr>
<tr>
<td>2</td>
<td>0.52</td>
<td>0.15</td>
<td>0.32</td>
<td>0.76</td>
</tr>
</tbody>
</table>

Comparing data from Table 3, solution 2 is dominated by solution 1 as solution 1 outperforms solution 2 in all 4 objectives. By going through all generated solutions, each solution is simultaneously compared across all its four
objectives. When it first encounters another solution which dominates it, the comparison process breaks, sorts the current solution into the dominated bin and moves on to compare the next solution. If there is no solution which dominates the current solution, it is sorted into the non-dominated bin. This process identifies non-dominated solutions which form the approximated Pareto front in 4-dimensions. Even when the number of objectives increase, the concept of dominance can still be applied to effectively generate an approximated Pareto front.

Non-dominated points are then substituted by a small three-dimensional visualisation of the solution on a 3D scatter plot representation of the data (see Figure 3, top-left). This helps with understanding each solution’s position across all 4 objectives and provides a quick feedback on the model design. Additional objectives can be represented by other visual properties like point size or outline colour. Still, some practical visualisation limitations occur as the number of objectives increase.

**Pareto front HDBSCAN solution clusters**

In addition to filtering out the approximated Pareto front of the design space, a clustering algorithm is applied to Pareto front solutions. Hierarchical density based spatial clustering of application with noise (HDBSCAN) is a clustering algorithm that can identify point clusters based on density and exclude outliers which might skew Pareto front analysis (Campello et al. 2013). It works by first constructing a minimum spanning tree based on mutual reachability distance—the maximum distance, out of the distance between adjacent points, and the distance between temporary core clusters of an arbitrary size. Distance based clusters are easily created based on this construct, many of them as children of larger clusters. By looping through clusters, the cluster tree is condensed by recursively reducing the reachable distance threshold between points. Lastly, HDBSCAN computes a cluster persistence value which is a metric to identify cluster stability. Stable clusters are then returned as a list of integer identifiers for each point. Points in cluster 1 or 2 would have an identifier of 1 or 2 respectively, while outliers would be identified by -1.

As dimensions increase, approximated Pareto front clusters become harder to identify by hand. As such, HDBSCAN can help in describing complex spaces as it disregards outliers and does not require a minimum cluster size or cluster group count. This provides an advantage over more common clustering algorithms like K-Means which require setting of a minimum cluster size; an almost impossible task, given the size of an arbitrary design space. Each cluster then forms an additional filter, focusing design space exploration from a previously large and complex one to a few groups of options.

**Part 2: Display of multiple objective values of a solution and the respective genotype values**

The second part of the visualisation tool focuses on displaying genotype of each solution. The aim is to allow designers to navigate through complex design spaces using genotype data. This helps to identify designs with similar genotype combinations, which are near to, but not along the approximated Pareto front.

Genotype values will be plotted on a parallel coordinates plot with normalised axes (see Figure 3, bottom). Objective values and other measurable quantities like site coverage and average building heights can also be added to the parallel plot. All axes will also be adjusted to have the upper limit of each axis represent desired values. Building on from the filters generated by the previous display, the various Pareto front clusters will be coloured to differentiate them from dominated solutions.

Parallel plots can be messy and provide limited insights besides overall data trend. However, a parallel coordinates plot can support brushing actions which allow a designer to sieve through the genotype data. Based on Pareto front clusters, one might be interested in solutions which have <500 kWh/m² solar radiation performance and <0.50 site coverage ratio. By highlighting the interested ranges along the various axis, solutions which satisfy the criteria are filtered out. Besides being allowed to identify said solutions, the designer can also study them side-by-side with identified Pareto front clusters.

**Part 3: Display of phenotypes and spatio-temporal simulation results**

The phenotype display is meant to provide designers with feedback on how the solution performs at a spatial level. Renderings of the solution and of its performance results expresses qualitative and quantitative performance information which aid decision making on aesthetic preferences or geometry response to site context. Spatial performance displays may also highlight problem areas and give a more nuanced understanding to the bulk objective function values. Coupled with the rendering are the simulation results, mapped onto the solution model. As such, design decisions can be made considering BPS results. For example, in solution 27 (see Figure 3, top right), an open space next to the commercial hub receives excessive amounts of solar radiation and possess a low wind score, thermal comfort is potentially low, making it unsuccessful as a vibrant public space. Solution 25 could be preferred if the designer stresses upon having an open area next to the commercial hub as it’s geometry provides more shade and gives a moderately high wind score, suggesting that thermal comfort is potentially high.

However, some designers might still prefer solution 27 as they might think that the framed public space has more potential in connecting the development to the commercial hub. By analysing the provided solar radiation spatial results, soft landscape strategies can be implemented to introduce shade, thereby improving thermal comfort.

Multiple phenotypes and their respective simulation results can be displayed at the same time, allowing an evaluation of results based on space function goals determined at the start of this computation design process, alongside performance data.
Figure 3: Three-part visualisation tool
Discussion

Despite the lack of constraints on the geometry generation for the example in this paper, contrasting performance outputs helped to sculpt results which suggest usable building forms. The Pareto front clusters also provide a good starting point for design space navigation, summarising overall design space into 2 focus areas and identifying outliers simultaneously.

Figure 4 shows how the Pareto front and HDBSCAN clusters help to drive design search as they narrow design space into a few high-performance solutions. In short, design search identifies solutions through objective values. Design space navigation refers to how a designer can use insights derived from the high-performance solutions to search for preferred genotype combinations within the larger design space. This navigation could be driven by qualitative design decisions like preferred building typologies or aesthetic preferences.

Figure 5 shows a portion of Pareto optimal results, which possess a high variety of forms. The various geometry suggests distinct types of spatial functions across the development.

Figure 6 shows solutions with 0 floor levels on the Eastern and Western parts of the site. Both solutions have similar objective values and urban scale forms. However, the cell makeup of each form suggests spatial variations at the building scale. The ability to visualise phenotypes alongside building performance data will allow design decisions to be made based on both architectural qualitative evaluation and quantitative building performance.

Conclusion

The authors propose a three-part visualisation framework that displays design space genotypes, phenotypes and the solution objective values. This provides designers with an organised data output from a previously complex multi-objective optimisation design space. Data filters to identify approximated Pareto front solutions through concept of objective dominance and HDBSCAN retain their effectiveness even when number of objectives increase, thereby supporting design space navigation.

Using multi-objective optimisation as a design tool

In a typical design problem, there are multiple design objectives which could drive the project in vastly different directions. The bulk of existing tools that support single objective optimisation generates results which are easy to understand as the evaluation and visualisation are based on a small sample of a generated design space and a single objective. Objective values of the best performing solutions often have minimal difference, making it difficult to extract insights for furthering design decisions. On the other hand, multi-objective optimisation results are formally diverse with a large spread of objective value.
combinations. This leads to a larger portion of the design space being explored which can potentially support better design decisions. A multi-objective approach also provides a better representation of design problems which usually involve a multitude of trade-offs. The proposed visualisation framework helps to organise a complex design space and its generated data. Generated solutions can then be evaluated based on objective value performance as well as spatial and aesthetic performance.

Although this paper only explored the use of building massing performance objectives, other objectives like structural costs minimisation or views maximisation can also be added to the process. Generated solutions can then be evaluated based on objective values which come from a larger range of design considerations. The concepts of performance dominance and HDBSCAN clustering to filter and focus design spaces are still applicable regardless of the number of objectives.

References


