Systematizing an Optioneering Approach in High Performance Building Design

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Abstract
Simulation-driven optioneering, involving various design decisions made in the early stages of design, is necessary to ensure all potential impactful High-Performance Building Design (HPBD) option iterations are adequately explored and communicated effectively. However, manually comparing design schemes to achieve an optimal balance between multiple competing Key Performance Indicators (KPIs) can be time-consuming so as not to oversimplify the design process required for a high-performance building.

To address these challenges, we have developed a set of customizable Grasshopper-based dashboards, including the MOO DASH (Multi-Objective Optimization Dashboard) detailed in this paper, leveraging parametric modeling, performance simulation, and data management to streamline, accelerate, and simplify the iteration and optioneering processes. These tools have been successfully implemented into various multi-scale projects and at different design stages, leading to timely comparisons of design options, optimization of design parameters, and shorter discussion times during the design optimization phase. Feedback from stakeholders has been positive, highlighting the effectiveness of these tools in HPBD design.

Highlights
- Scheme comparison and design optioneering based on the Multi-Objective Optimization techniques
- Net Zero Carbon and High-Performance Building design optimization workflow
- Customizable interactive dashboard developed within the Grasshopper scripting platform
- Methodology practices and tool implementations on multi-scalar projects and at different design stages

Key Innovations
- The MOO DASH enables the visualization of the full stack databases with building performance simulation results, which increases visibility and engagement.
- The MOO DASH provides script-based customizable functionalities to support proceeding MOO techniques, allowing maximum adaptability across different projects.
- The MOO DASH streamlines the iterative design optioneering workflow, which simplifies decisions on performance-driven design parameters

Practical Implications
The evidence-based and performance-driven design recommendations shall balance multiple KPIs together while prioritizing the cost impacts when optimizing for low-carbon and high-performance options. We shall facilitate the multiple stakeholder engagements by augmenting the discussions with user-friendly data visualizations, as well as avoiding efforts on those design parameters with little effect on building performance.

Introduction
A High-Performance Building Design (HPBD) is a process-oriented framework to achieve measurable performance goals for Net Zero Carbon, energy and water efficiency, and occupant health, comfort, and well-being. It requires identifying and integrating an optimal strategy bundle from a vast array of options, rather than just a limited few. Early decisions on key design drivers heavily impact both the efficiency of the design process and the overall performance of a delivered building (Clevenger, 2014). It is challenging to adequately explore and communicate all potentially impactful design solutions early in the design process, especially when dealing with mutually exclusive objectives, as well as a lack of adequate time.

An iterative and fast-paced process is essential to evaluate the sensitivity of performance to design measures. However, the setup, modeling, and analysis of multiple iterations are time-consuming, which limits such comprehensiveness to a small fraction of HPBD projects. Additionally, a design optioneering stage is important following the iterative process, to validate the recommendations. Optioneering is the leveraging of mathematical techniques to optimize multiple objectives simultaneously. One big challenge during optioneering is to find trade-offs between competing objectives.

The scripting platform Grasshopper incorporates a wide range of performance simulation tools, through 3rd-party libraries. Parametric modeling with these tools affords opportunities to explore a wide range of design variables and to assess performance with them. To leverage this computational ability, we have been developing a collection of Grasshopper-based dashboards - with the MOO DASH (Multi-Objective Optimization Dashboard) highlighted in this study - to streamline, accelerate, and simplify the iteration and optioneering processes (Azagury, 2020).
We seek to systematize an optioneering approach which is a structured and repeatable process for leveraging computational methods to find the best design solutions, including identifying objectives, defining constraints, selecting appropriate design variables, and using MOO algorithms to find the best trade-offs between competing objectives (Deb, 2016). This approach can help streamline the optioneering process and ensure consistent and optimal design decisions.

**Literature Review**

Multi-objective optimization (MOO) is a technique that helps to optimize several objectives at the same time by finding an optimal solution that either minimizes or maximizes each objective (Gunantara, 2018). MOO has gained significant popularity in the field of building simulation. The process of MOO has been facilitated by the development of various tools such as One Click LCA, Insight 360, Design Explorer, Octopus, and WALLACEI. These tools assist in the optimization process by providing graphical user interfaces, algorithm integrations, and automation that allow users to explore the design space rapidly and effectively.

One Click LCA (LCA), for instance, provides a user-friendly interface that allows users to set objectives and constraints and evaluates design options dynamically (Al-Obaidy, 2022). Insight 360 (Insight) is a cloud-based simulation tool that can be used to optimize building designs based on different criteria such as energy efficiency, comfort, and cost (Autodesk, 2020). Another tool that has gained significant attention is Design Explorer (D.E.), which is a software framework that enables users to explore and compare different designs based on multiple objectives (Reyes-Lecuona, 2017). Octopus (Octps.) is a popular MOO software that focuses on optimizing building design parameters to achieve low-energy consumption and thermal comfort (Jazizadeh, 2019). Finally, WALLACEI is a computational tool that uses evolutionary algorithms to optimize building designs based on specific objectives and constraints such as building orientation, form, and material efficiency (Mirjalili, 2018).

These tools have significantly improved the decision-making process in building design, particularly in the early stages. However, each tool has its own limitations and gaps, which are shown in Table 1.

| Table 1: Gap analysis of multiple MOO tools |
|-----------------|-----------------|-----------------|-----------------|
| **Performance Simulation** | LCA | Insight | D.E. | Octps. |
| Visualize external data | Include | Include | NA | NA |
| # of iterations | 1-10 | 10-100 | No limit | No limit |
| Iteration generation | Manual | Auto | Auto | Auto |
| Optioneering process | Manual | Manual | Auto | Auto |
| Evaluation effort | Low | Medium | Medium | High |
| Integrated collaboration | High | High | Medium | Low |

In summary, the reviewed MOO tools offer graphical user interfaces that enable users to explore the design space efficiently, which enhanced the optimization of multiple objectives in building design. However, they also have specific scopes and limitations that should be considered when selecting the appropriate tool for a particular project. Further advancements in MOO approach are necessary to overcome these limitations and provide more comprehensive and integrated solutions for building design optimization. There remains a need for a comprehensive platform that can integrate and synergize the aforementioned efforts. This platform should encompass a wide range of project types and performance analyses, while also offering guided workflow to assist users in identifying the optimal design solution.

**Methods**

Systematizing an optioneering approach in HPBD represents an evolitional methodology built upon the primary techniques of Collibri and Design Explorer, which offers several advantages, including:

- No limitations on the number of iterations
- An automated iteration generation process
- An interactive dashboard

However, to further enhance the method and make it accessible to professionals with basic backgrounds, we propose incorporating additional features that manage complexity while maintaining ease of use, including:

- High flexibility in changing the optioneering tool interface for adaptability and scalability
- Interpretable performance results to support right-sizing the amount of decision
- Reduced optioneering efforts for affordable studies within limited project schedules

The proposed optioneering workflow is organized into three key components, ensuring consistency, flexibility, and scalability:

1. Standardized workflow to maintain consistency in the MOO process, enabling efficient execution and streamlined decision-making.
2. Right-sized solution to ensure that the solutions align with project objectives while avoiding unnecessary complexity or over-engineering.
3. Customizable dashboard to allow users to tailor the interface to their specific needs, thereby enhancing usability and interpretation of performance data.

**Standardized Workflow**

A standardized optioneering workflow is recommended for all HPBD projects to ensure consistent project delivery. It is critical to agree with project stakeholders on the methodology, design parameters, and optimization objectives before commencing the MOO process and proposing design solutions.

The typical workflow is displayed in Figure 1. It includes the following steps:

- **Analyze - Objective Determination.** The first step is to define challenges and formulate measurable objectives with their preferred weighting criteria to inform the
optioneering trajectory. A high-level cross-disciplinary analysis is conducted on the local design drivers, including environmental conditions, human preferences, and project budget - along with code requirements and space allowance.

Figure 1: A typical design optioneering workflow proposed in HPBD.

Prototype - Parameter Definition. Prototyping is to parametrically set up a geometric model and use it to define the variables with their constraints, which include geometric dimensions, logic (e.g. shade or no shade), material properties, and system inputs. Properly determining these parameters is critical to the reliability of the MOO results.

Evaluate - KPI Quantification. The design metrics must be quantified through building performance and environmental simulation, most of which are traditionally simulated in non-parametric stand-alone tools, such as Ecotect, IES-VE, and One Click LCA. The proposed workflow requires all KPIs to be evaluated parametrically on the same platform. Some parametric tools under rapid development, such as Ladybug Tools, are preferred to be utilized. In these tools, design parameters are connected as inputs into the base model and the outputs are exportable and editable that can be further analyzed.

Optimize - Design Solutions Finding. The final step is to find the recommended solution based on their quantified performance through one of the MOO solutions. We will discuss the four typical approaches in different Tiers to support the finding process in the next chapter.

Right-sized Solution

Selecting the appropriate right-sized optioneering solution is of importance to strike the right balance. It should neither be overly simplified, which could risk missed opportunities, nor overly complicated, which could result in misinterpretations. This careful selection ensures the affordability of the study in real practices.

Optioneering refers to the process of searching for better design solutions, typically involving a set of solution bundles, rather than a single solution, on the Pareto frontier, by maximizing or minimizing the selected KPIs, also known as Objectives. A MOO process is known as the optioneering with a minimum of two conflicting objectives identified, such as minimizing energy while maximizing daylight. The main challenge is to identify the best trade-offs between multiple competing objectives.

Figure 2 shows the four approaches to conducting MOO. We categorized them based on complexity and applicability, starting from the most straightforward and commonly used to the most extensive.

- Tier 1: Design Bundles
- Tier 2: Parameter Sensitivity
- Tier 3: Full-Stack Database
- Tier 4: Genetic Algorithms

Tier 1 involves comparing a small number of design bundles – typically from two to five bundles – between each other or against the set baseline. This is a common request at the early design stage. The performance impact differences can be quickly presented by manually adjusting the design parameters and running the simulations sequentially. The process continues until a satisfactory solution is agreed upon by the stakeholders or the project phase ends. One example is to compare two façade material options to find the one with lower embodied carbon impacts using One-Click LCA software. However, due to the limited number of iterations that can be simulated and evaluated, the actual best or most balanced solutions might be missed.

Tier 2 involves sensitivity analysis of the proposed design variables to identify the most significant opportunity for building performance improvement. This also avoids wasting efforts on design parameters that have a negative impact or little effect on building performance. This approach efficiently provides directional design parameter recommendations for each building component in feasibility studies or design guidelines when multiple design variables need to be tested without the need for precise results. Autodesk Insight 360 software is one of the HPBD tools that employ this mechanism.

Tier 3: Providing a full-stack database with the simulation results for potentially impactful design options, typically ranging from hundreds to thousands of iterations, maximizes the opportunity to find the best solution by exploring all potential variations. This approach is highly transparent, engaging stakeholders and producing the most acceptable design optioneering approach in professional practices, given sufficient time and budget. While the manual process is time-consuming, automating the process of recording simulation results into a full-stack database for further analysis is always requested. Visualizing data through open-source tools, such as

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typical GA process includes the following steps:

- A set of initial solutions are randomly generated with their performance evaluated iteratively.
- The optimization in each subsequent generation is based on the most favorable outcomes of the previous generation, considering the set objectives.
- This linear search-and-optimization will continue until the number of generations reaches the “max generation”
- The best-fitted instances shown on the Pareto Frontier are considered the most optimal solutions.

Octopus (Jazizadeh, 2019) and Wallacei (Mirjalili, 2018) are two popular plug-ins for Grasshopper that leverage GA to solve MOO problems parametrically. These tools automate the iterative process and present the results of all generations in an independent solution space, distributing all the solutions in a coordinate axis view.

The four tiers of Multi-Objective Optimization (MOO) provide different levels of complexity and applicability. Selecting the most appropriate MOO approach according to the specific project requirements and available resources and applying it in a validated workflow are the keys to finding the best performance solution.

In professional practices, this optioneering process will almost always be terminated before it reaches one optimal solution due to time constraints. Therefore, Tier 1 and Tier 2 are adopted in most business-as-usual situations. Even if Tier 3 with a full-stack database provided maximizes the opportunities. It is critical to automate the process and allows people to efficiently filter and sort the data points and guide the selections according to the pre-identified design objectives and customized weighting criteria. A proposed digital method will be presented in the next chapter.

**Customizable Dashboard**

The Tier 3 design optioning process with a full-stack database request typically demands enormous time to generate numerous design options. Many Grasshopper plugins have already been widely implemented in the industry to parametrically prototype the models, quantify the performance, and automate the process individually. For example, the quantified simulation results of the design iterations can be exported into an editable database through Colibri if the script is well connected with simulation engines. Chances are automatically generated, evaluated, recorded, and visualized onto an interactive chart to support finding the solution. Figure 3 shows a snapshot of the exported database through Colibri with both inputs (Design Parameters) and outputs (KPIs) automatically recorded.

However, there is a lack of a customizable platform to provide a user-friendly interface to guide finding the optimal design solution from the database. The visualization shall include the following features:

- Selecting and de-selecting the inputs and outputs.
- Allowing filtering of the inputs and outputs.
- Allowing highlighting the solutions and showing the performance difference between each other.

We have been developing MOO DASH, which is scripted in Grasshopper, to address the issue. Two infographics approaches have been tested to resolve the complexities: Parallel Coordinates and Scatterplot Coordinates.

The Parallel Coordinates chart is a widely-used infographic for representing the MOO data, as used in Design Explorer (Reyes-Lecuona, 2017). It visualizes n-variables and KPIs in the same chart by adding n parallel vertical axes, with each axis representing a variable or KPI. Each data element is displayed as a series of connected points along the measure/axes connected by a polyline, corresponding to a tested iteration or solution.

Users can highlight specific scenarios by selecting key inputs to compare values. The chart highlights specific patterns of association on different axes, which makes it easy to compare and contrast the trend between variables, but it may be difficult to interpret relationships when there is no clear linear consistency observed between the axes. As a result, it may not help find the best design solution.

Scatterplots are useful for showing large quantities of data and correlations between variables and KPIs. However, scatterplots may not be suitable for presentations as users are typically bad at interpreting the results quickly, especially if there are too many data points or more than two objectives. They can also be problematic if the data is too spread out or overplotted to see clear patterns, so it’s important to be aware of these issues when using scatterplots for analysis or presentation.

MOO DASH is the tool to interactively streamline the design optioneering using a Scatterplot chart and find the best trade-off from numerous iterations. Figure 5 shows the current user interface design with the main functionalities highlighted.
1. The main window shows the scatterplot with all the tested scenarios visualized.

2. Two primary KPIs driving the decision makings are identified as those dimensions placed on the vertical axis and the horizontal axis.

3. Points represent every piece of data on the chart. Variations on scatterplots introduce differently shaped or colored points for additional dimensions.

4. Select and de-select the inputs (in:variables) and outputs (out:KPIs) and map them to five dimensions: X(X axis), Y(Y axis), C(point color), S(point scale), and G(point shape) to suit different comparison logics in different projects.

5. Filter the inputs (in:variables) and outputs (out:KPIs) to narrow down the applicable scenarios.

6. Set the optimal boundary based on the objectives of the two primary KPIs: scenarios within the boundary are considered as optimal solutions.

7. Highlight two solutions and visualize the performance difference between each other.

Results

Three professional case studies demonstrated the advantages of implementing the systematic optioneering process based on Tier 3 MOO over conventional design optioning process based on Tier 1 MOO. The experiments encompassed multi-scalar HPBD components, ranging from optimizing conceptual massing and orientation, configuring façade exterior shades, and identifying optimal building envelope insulation R values and low-carbon insulation products.

The initial outcomes demonstrated that utilizing digital tools to support the systematic design optioneering process enables the evaluation of six to nine times more iterations within a maximum of twice the study time. The reliable results extracted from the comprehensive option database guarantee the quality and precision of the building’s performance upon project delivery.

Table 2: Summary of the total iteration numbers using Tier 1 MOO and Tier 3 MOO studied in the Test Cases

<table>
<thead>
<tr>
<th>Test Case</th>
<th>Test Case I</th>
<th>Test Case II</th>
<th>Test Case III</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable Number</td>
<td>3</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>Iteration Number of each Parameter</td>
<td>3</td>
<td>3</td>
<td>6</td>
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<tr>
<td>Total Iteration Number in Tier 1</td>
<td>3</td>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td>Total Iteration Number in Tier 3</td>
<td>81</td>
<td>81</td>
<td>36</td>
</tr>
</tbody>
</table>

Test Case I: Massing and Orientation Optimization

Test Case I is to identify the best massing and orientation option for a three-story lab building in Denver through a two-round optioneering process (Figure 6). During the first round, the design team proposed three options: Option A: double-loaded; Option B: single massing with a centralized atrium; Option C: single-loaded.

We then further analyzed Option A in the second round, adding three variable, including deviating and rotating the bars independently and kinking the geometry up to 20 degrees from the middle point. In total, we define 81 design schemes in the second round.

The performance outputs shall not require additional input details beyond building functions, weather files, and surrounding contexts. These outputs may include heating and cooling load, daylight distributions, solar generations, and simple capital costs.

In this test case, we identified two primary objectives: find the massing with the lowest space Energy Use Intensity (EUI) while ensuring that the sDA at the working surface level is at least 75%. By achieving these objectives, the project has a greater chance of receiving three points in the LEED Daylight credit and more points in the Energy credit. These objectives are displayed on the X and Y axes of a scatterplot chart. When selecting the optimum massing options, cost premium (displayed as different sizes) is considered a secondary objective when...
selecting the optimum massing options. The green zone highlights all applicable options.

The process enabled the team to select the optimal massing (Option A3), which had lower energy, improved daylight, and lower cost than the original massing (Option C) and the current design (Option B3). This massing features a 20-degree kink in the middle of the building and the south bar is positioned closer to the North bar.

**Test Case II: Façade Optioning and Optimization**

In Test Case II, we assisted the facade optimization by fine-tuning the external vertical fin dimensions on each facade of a commercial tower in Wenzhou, China. The design team proposed three feasible options for external vertical fin depths for each facade (150mm, 400mm, and 600mm), resulting in a total of 81 defined facade schemes.

The process was divided into two stages. During Stage 1: Optioning, we conducted a rapid comparison of the performance variance between up to four facade schemes of an identified typical bay using preliminary energy modeling and daylight simulation. By utilizing the FIT (Façade Impact Tool. Figure 7), another internally developed digital platform, we were able to complete this process within two hours. This tool can evaluate other parameters, including Window-to-Wall Ratio (WWR), fenestrations, balanced wall assemblies thermal properties, material selections, shading devices, and Building Integrated Photovoltaic (BIPV) configurations.

In Stage 2: Optimization, we identified two primary objectives: first, to minimize the space Energy Use Intensity (EUI), and second, to ensure that the Simple Payback Years, does not exceed 30 years. These objectives were exhibited on the X axes and Y axes of the scatterplot chart, with the cost premium and Useful Daylight Index (UDI) being considered secondary objectives (Figure 8).

Based on the findings, the most optimal fin sizes with lower energy, better daylight, and accepted cost premium and the payback years were determined to be 150mm fins for the southern/northern facade and 600mm fins for the eastern/western facade.
Test Case III: Insulation Sensitivity Analysis

The third test case is a 280k sq.ft. transformational Net Zero Carbon (NZC) Logistic Center prototype design across multi-climate zones. The client requested to analyze the impact of different roof and wall insulation R values on energy, carbon, and cost beyond the code minimum requirements. They asked for recommendations on the adjusted R values for buildings in three different climate zones. It was agreed that increasing insulations for both roof and walls might not lead to the best performance and proposing such strategies could trigger cost issues due to significant capital cost premiums and unacceptable payback years. However, the exact combinations of R values remained unclear.

We identified 36 insulation options (6 roof options x 6 wall options) in each climate (Table 3 and Table 4). The Reduced, Base, Good, Better, and Best are defined by the insulation R values, so they should not be considered Recommendations. The recommended insulation options are presented as the conclusions of the MOO process.

Table 3: Roof Insulation Options U Values Btu/Hft2F

<table>
<thead>
<tr>
<th>Roof U</th>
<th>Atlanta</th>
<th>Seattle</th>
<th>Minneapolis</th>
</tr>
</thead>
<tbody>
<tr>
<td>N/A</td>
<td>0.680</td>
<td>0.680</td>
<td>0.680</td>
</tr>
<tr>
<td>Reduced</td>
<td>0.044</td>
<td>0.030</td>
<td>0.035</td>
</tr>
<tr>
<td>Code</td>
<td>0.039</td>
<td>0.027</td>
<td>0.032</td>
</tr>
<tr>
<td>Good</td>
<td>0.036</td>
<td>0.025</td>
<td>0.030</td>
</tr>
<tr>
<td>Better</td>
<td>0.033</td>
<td>0.024</td>
<td>0.027</td>
</tr>
<tr>
<td>Best</td>
<td>0.030</td>
<td>0.023</td>
<td>0.025</td>
</tr>
</tbody>
</table>

Table 4: Wall Insulation Options U Values Btu/Hft2F

<table>
<thead>
<tr>
<th>Wall U</th>
<th>Atlanta</th>
<th>Seattle</th>
<th>Minneapolis</th>
</tr>
</thead>
<tbody>
<tr>
<td>N/A</td>
<td>0.625</td>
<td>0.625</td>
<td>0.625</td>
</tr>
<tr>
<td>Reduced</td>
<td>0.140</td>
<td>0.115</td>
<td>0.087</td>
</tr>
<tr>
<td>Code</td>
<td>0.123</td>
<td>0.104</td>
<td>0.080</td>
</tr>
<tr>
<td>Good</td>
<td>0.087</td>
<td>0.087</td>
<td>0.066</td>
</tr>
<tr>
<td>Better</td>
<td>0.075</td>
<td>0.069</td>
<td>0.052</td>
</tr>
<tr>
<td>Best</td>
<td>0.060</td>
<td>0.057</td>
<td>0.044</td>
</tr>
</tbody>
</table>

Multiple KPIs were originally identified as the optimization objectives to support the decision-making:
- Lifecycle Embodied Carbon (EC) Savings
- 15-year Operational Carbon (OC) Savings
- Preliminary capital expenditure premium
- Annual energy cost difference
- Preliminary simple payback years

We simplified the list and confirmed only two primary KPIs and their targets to facilitate the process.
- Simple Payback shall be less than 5 years
- Maximize Lifecycle Carbon Savings (EC + OC)

Each insulation scenario (roof option + wall option) generated was automatically recorded through Colibri and populated as polygons onto a scatterplot chart in MOO DASH. The wall insulation R values are displayed as different polygon shapes, and the roof insulation R values are displayed as different sizes of polygons.

The objectives are displayed on the X axes (EC+OC Savings) and Y axes (Payback) of the scatterplot chart. We first filtered out all insulation scenarios with Payback over five years, then picked the scenario with the highest EC+OC Savings within the filtered option list.

Discussion

In general, the development of a visual interface over a computational MOO framework makes the optimization process rapid, iterative, and yet simple and easy to follow.
The parametric process automates the prototyping, simulation, and optimization procedures, enabling quick adjustments that facilitate design changes. Advanced automation is the cornerstone of saving human hours and reducing costs, making design optioneering during the early stages less burdensome and more impactful.

By furnishing an integrated process with consistent modeling settings as inputs and a data visualization format on the output side, the involvement of project stakeholders is also facilitated. Lastly, this approach also fosters collaboration among different design disciplines while directionally validating the building performance at the early stages.

This customizable tool showcases the flexibility of the approach, making it suitable for application in various design projects with different variables, KPIs, and optimization objectives. It aids in visualizing and interpreting the excel-based database. The components can be manually selected and de-selected to prioritize different criteria, strategies, or disciplines.

Two main challenges were encountered in all three test cases. To assist in the selection process when deciding between the schemes with competing objectives (i.e., maximizing daylight while minimizing energy), additional cap boundaries were introduced, such as the maximum cost premium and the minimum Payback Years. This proved beneficial in narrowing down the set of optimal solutions on the Pareto frontier mesh into one.

On the other hand, although there are no apparent limitations to adding more inputs (variables) and outputs (KPIs), a practical approach is required to achieve trade-offs effectively. The studies have proposed three approaches to address the challenge of dealing with more than two objectives in the optioneering process.

- **Approach 1** Set priority sequence in selection. This approach involves defining a priority sequence for objectives and systematically eliminating suboptimal options until the best solution is found. This approach was applied in Test Cases I and II.
- **Approach 2** Determine the key objective or combine metrics. This approach involves selecting or combining multiple metrics into two most critical objectives to simplify the decision-making process. This approach was used in Test Case III.
- **Approach 3** Add weightings to calculate the overall score of multiple KPIs. This approach involves assigning weights to each objective to calculate a total score and select the solution with the highest score.

Since the current digital scripts are still stored on local computers, which restricts access for multiple collaborators, the energy and daylight simulation speed is dependent on the computational power. Hence, future work is required to explore decentralized computing methods, leverage machine learning to extrapolate and project the results without actual simulation, and develop a web-based MOO interface.

### Conclusion

This paper emphasizes the importance of MOO analysis in achieving optimal design solutions that meet multiple objectives within the constraints of the project’s timeline. The proposed approach provides a standardized workflow that maintains consistency enabling efficient execution. The emphasis on right-sized MOO solutions ensures that objectives are met without unnecessary complexity. Additionally, the customizable dashboard enhances usability and facilitates better interpretation of results. This paper also illustrates the above points by showcasing the results of MOO DASH test cases, that contribute to the advancement of sustainable design.

### References


