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EVALUATING THE MULTI-OBJECTIVE OPTIMIZATION METHODOLOGY FOR PERFORMANCE-BASED BUILDING DESIGN IN PROFESSIONAL PRACTICE

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ABSTRACT

This paper examines the applicability of a Multi Objective Optimization (MOO) methodology within a parametric design setup. The primary focus of MOO is to facilitate early stage decision making in professional High Performance Building (HPB) practice. With environmental variables and objectives stemming from all design disciplines, there is a need for designers and engineers to work together to capitalize on their varied expertise and achieve efficiencies in HPB design optimization. This paper outlines two experiments carried out using the Octopus plugin, which is a MOO solver, within the Grasshopper (GH) parametric design interface. The findings show promising outcomes, highlight potential opportunities, and identify limitations of the proposed methodology.

KEYWORDS

Multi-objective optimization, early stage design, high-performance building design, inter-disciplinary collaboration.

INTRODUCTION

As building designers focus on minimizing their design's environmental impact, they often face conflicting criteria as shown in Figure 1. In the traditional design process, simulations are critical to evaluating the buildings' performance in the areas of environmental impact and capital viability; energy usage and human comfort; indoor air quality and fan power consumption; or thermal load and daylight levels. In early stages of design however, conducting repeated evaluation iterations can be time-consuming and costly.

To maximize the value of building performance analyses conducted, designers have turned to Multi-Objective Optimization (MOO). MOO is a parametric and generative design methodology which enables the rapid exploration of alternative options and the computational assessment of trade-offs between environmental performance, energy consumption and capital expense.

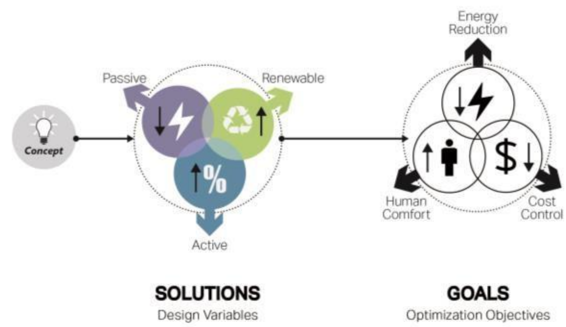

Figure 1: Conflicting Criteria during HPB Design

A typical MOO process requires one or more simulation engines connecting to multiple variables as the inputs and multiple objectives as the outputs. When leveraging MOO in HPB design, the most commonly optimized objectives are a) energy performance and b) construction cost (Attia et al, 2013). Examples of input variables used include massing dimensions, envelope properties, system types and controls. The speed at which a design solution can be found through the MOO methodology depends on the computational power available to the designer and the ability of their tool to effectively manipulate the input parameters.

An additional challenge to the application of MOO in HPB professional practice can be the lack of coordination between disciplines in the early stages of design. HPB design should ideally be based on a comprehensive understanding of multi-disciplinary design parameters for enhanced building performance; and therefore requires an integrated approach that meshes together cutting-edge architectural design with state-of-the-art mechanical systems. However, most traditional MOO applications focus either exclusively on architectural elements, or on HVAC system options, conducting separate optimizations for each and at different times during the design process.

One potential reason for this isolation is the existing limitations on the MOO tools available. While there is a wide range of MOO tools and optimization algorithms available, these tools are not generally integrated with simulation and visualization software which adversely impact the user experience. The rapid development of genetic algorithms (GA) and machine learning tools for MOO applications, such as GH and Dynamo, is bridging the gap between optimization and visualization; and is opening possibilities for inter-disciplinary collaboration.

DEFINITIONS

Multi-Objective Optimization: The use of mathematical techniques to simultaneously optimize more than one objective subject to pre-determined constraints.

High Performance Building Design: The process of designing low energy and carbon footprint buildings with high indoor air quality and thermal comfort in comparison to conventional building designs.

Pareto Optimal: A solution whose performance in response to a given problem is equal to all other available solutions, i.e. is non-dominated and non-inferior.

Octopus: A GH plug-in which applies evolutionary principles and multi-objective optimizations to parametric design.

Genetic Algorithm: A type of evolutionary algorithm which uses natural selection principles on a population and its subsequent generations to identify multi-objective solutions with the most optimal characteristics.

BACKGROUND RESEARCH

The concept of multi-objective optimization is considered to have been developed in the late 19th century by Francis Y. Edgeworth and Vilfredo Pareto with its initial applications in the field of economics (De Weck, 2004). Pareto's work popularized the concept of the Pareto Optimal, the point at which any change would result in benefits to some and detriments to others.

The notion of Pareto Optimal solutions began to be commonly applied to Engineering and Design problems after 1970 (De Weck, 2004). As optimization algorithms and software tools became available to the design industry, the applicability of MOO extended beyond traditional engineering fields and began being used in the fields of architecture and building system design.

Architectural Design

There are many instances in literature showcasing the MOO methodology being applied to the architectural aspect of HPB design. The building architectural components whose performance is evaluated using the MOO approach include the façade morphology, envelope material selection and layer thicknesses.

Two notable studies conducted by Gagne and Andersen, 2010, and Rahmani Asl et al, 2014, focused on the use of MOO in the optimization of façade morphologies for daylight penetration and glare control. In the former, the authors ran the optimization process in SketchUp 3D-modeling software, while the latter developed codes and scripts in Dynamo for Revit. Both required designers to export data to standalone environmental simulation engines such as Lighsolve Viewer (LSV) or Green Building Studio Run (GBSRun) and conduct MOO separately. Other studies have used MOO to co-optimize the building energy performance and construction cost reduction (Vilcekova et al, 2014).

Building System Design

A separate body of research has focused on applying various multi-objective optimization approaches to heating, ventilation and air conditioning (HVAC) design. In this context, MOO has been used as part of a generative design process to optimize building thermal zones, type and location of air supply and return grills, duct routing and equipment sizing using MATLAB (Berquist et al, 2017). In HVAC-focused simulations, typically the goal is to minimize building energy consumption and construction costs, as is the case with envelope optimizations. Similar objectives were used in a MOO simulation of a single-family home HVAC system design (Hamdy et al, 2010).

Comprehensive Studies

The consensus in the industry is that evolutionary algorithms, also known as genetic algorithms, will significantly improve the computational effort required for MOO and will allow designers to address a wider range of design problems (Attia et al, 2013). Genetic algorithms have been used for sequential optimization of architectural and HVAC system design with promising results (Caldas et al, 2003), but there is still room for development of integrated MOO applications to conduct simultaneous evaluation of these parameters and optimize their impact on building performance and construction cost.

METHODOLOGY

Employing a MOO approach within a parametric design setup is a critical step towards achieving a successful optimization within HPB design. To bridge the gap between architectural design and other building elements, using a 5-step workflow is proposed: Analyze, Prototype, Evaluate, Evolve, and Select.

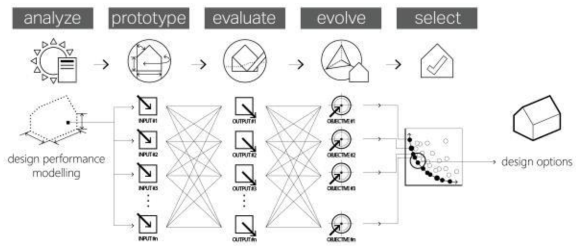

Figure 2: Proposed Workflow

Analyze: Objective Determination

The first step is to define problems and formulate objectives. A cross-disciplinary analysis is conducted on the local design drivers -environmental conditions, human preferences and project budget- along with code requirements, cost, and space allowance. The analysis conclusions including design strategies, parameters constraints and preferred weighting criteria inform the future trajectory of the design and the optimization objectives. All objectives must be quantifiable or measurable for the MOO algorithm tools to effectively simulateand explore every iteration.

Key objectives in HPB design in professional practice include daylight, energy and cost. Daylight level and energy consumption can be simulated through existing parametric tools which are ready for carrying out MOO. Other metrics such as energy, cost, and embodied carbon can be calculated in non-parametric programs and require a linking platform.

Prototype: Parameter Definition

Prototyping is the step in which both the variables and the fixed parameters are defined. A geometric model is parametrically setup as the baseline for evaluation.

The variables can include geometric dimensions (e.g. massing orientation), logic (e.g. shade or no shade), material properties (opaque and glazing U-factors), and system inputs (e.g. heat resource), within the limitations of the parametric design software. The fixed parameters are generally given by the contextual analysis (e.g. site location), architectural principles (e.g. room size), and code requirements (e.g. air exchange rate). The proper determination of these fixed constraints is critical to the reliability of the MOO results in professional practice.

Currently, prototyping is preferably performed in one of the following parametric modeling software: GH/Rhino and Dynamo/Revit. Models are parametrically generated and connected to one or more available environmental simulation software for performance evaluation. The range of each variable is carefully predetermined based on design constraints.

Evaluate: Building Performance Simulation

The design metrics need to be quantified through building performance simulations, which requires designers and engineers to use multiple computational tools to conduct dynamic thermal simulations, life cycle cost analysis, and embodied carbon calculations. Two simulation types are the focus of the paper: Environmental Performance Evaluation and Building Energy Modeling.

The Environmental Performance Evaluation is the primary type of simulation for MOO in developing passive design strategies through daylight simulation, glare study, and thermal analysis. Building Energy Modeling tests how building envelope and mechanical system types affect energy consumption. Most evaluations are traditionally simulated in non-parametric stand-alone tools, such as Ecotect, IES-VE and eQuest.

The proposed MOO approach requires all objectives to be evaluated parametrically and holistically on the same platform to promote both design automation and collaboration. Some parametric tools under rapid development, such as DIVA and Ladybug Tools, are preferred to be utilized.

In the parametric simulation tools, variables and fixed parameters are connected as inputs into the base model. The outputs are usually heat map meshes for visualization and editable data lists that can be further analyzed, sorted and filtered when linked to GA tools.

Evolve: Design Solutions Generation and Evolution

To enhance the optimization process, a larger number of solutions need to be evaluated within a shorter period. This demands that MOO be integrated earlier in the design process and be more easily accessible to designers and engineers.

Octopus is proposed as the automatic parametric MOO solver in the methodology. Instead of manually modifying every input, enabling the run button in sequence, and comparing results one by one, the entire process is automated by a single click when both the variables and the functions are properly connected to the engine. A typical GA process in octopus includes the following steps:

1. A set of initial solutions are randomly generated and their performance is evaluated iteratively. The maximum number of solutions in each generation is defined as "population size".
2. The optimization in each subsequent generation is based on the most favorable outcomes of the previous generation, considering the objectives.
3. This linear search-and-optimization will continue until the number of generations reaches the "max generation" pre-set by the user, or until the user terminates the process.

Select: Design Solutions Sorting and Finding

In professional practice, the optimization process will almost always be terminated before it reaches one optimal solution due to time constraints. The best result cannot be considered as an individual answer, but as a set of solution bundles on the pareto frontier.

To obtain a single "best" bundle in professional practice, the biggest challenge during the selection is to find the trade-offs between two or more competing objectives. Therefore, the final step is to filter and sort the optimum solutions set, according to the customized weighting criteria. Two effective visualization approaches for data organization can be used to resolve the complexity of the problem: 3-D coordinates and Parallel Coordinates.

Octopus automatically visualizes the results of all the generations in its own solution space. A maximum of five objectives can be visualized in the space as 3-D coordinates in addition to color and size. While all the solutions are distributed in the coordinate axis view cube, the best-fitted instances are shown on the pareto frontier mesh. Results can also be exported back to GH to customize other types of parallel coordinates plots and distribution charts.

Parallel Coordinates, adopted by Design Explorer, is one of the most widely used MOO sorting programs and a common way to visualize variables and objectives in the same chart by adding multiple axes. The multi-dimensional problem can therefore be collapsed into a 2D pattern making solution-finding easier.

EXPERIMENTS

To demonstrate the methodology discussed above, the authors conducted two experiments, named A and B.. Experiment A focused on multi-objective optimization of architectural aspects of a building. It included daylight penetration and glare analysis using software such as Grasshopper, DIVA, and Octopus. Experiment B expanded upon Experiment A by adding a third objective; the minimization of Energy Use Intensity (EUI) in kBtu/ft2, and included two HVAC system types as variables. Honeybee was used due to its capabilities on both daylight and energy modeling simulation.

Experiment A: Objective

The objective of Experiment A was to arrive to a set of pareto optimal solutions for window-to-wall ratio (WWR), shading type (horizontal or vertical) and shading depth for each facade and each floor within a sample building; such that both the following conditions are simultaneously true:

A. Maximize Daylight Penetration: Minimize sensors with daylight lux levels below 300 lux at both 9 AM and 3 PM.

B. Minimizing potential for glare and direct heat gain: Minimize sensors with daylight lux levels above 2000 lux at both 9 AM and 3 PM.

Experiment A: Setup

A laboratory building located in San Francisco, CA with a total floor area of 26,000 ft2 was modeled using Rhinoceros 3D modeling software and Grasshopper plugin. Only the geometries directly affecting the two objectives, such as facades, windows and shading, were parametrically constructed. The model also included trees and neighboring buildings.

Parameters controlling window dimensions, type of shading and shading depth were setup to vary within predetermined limits set based on design constraints.

The initial iteration of the building was connected to DIVA daylight simulation software. Sensors were placed at a 12-inch square grid. Two daylight simulations were carried out to get Illuminance levels at 9 am and at 3 pm at the design day. Colored Illuminance maps and numeric values of lux levels on each floor were output.

Octopus was selected as the MOO solver for this experiment. To prepare the parametric model generated for MOO, the variables were connected to Octopus as genes and the outputs were connected to Octopus as objectives. Octopus introduces multiple fitness values to the optimization and uses a genetic algorithm to conduct the optimization. The MOO settings selected are shown in Table 1, and the generations were capped at 20.

Table 1: MOO Octopus Settings

MOO TYPE	HYPE
Elitism	0.500
Mutation Probability	0.100
Mutation Rate	0.500
Crossover Rate	0.800
Population size	50
Maximum Generations	20

Experiment A: Outcomes

Octopus searched the best trade-offs between the two objectives, producing a pareto frontier graph for each set of solutions in each generation. Figure 3 shows a 2D pareto frontier after the generation number 20.

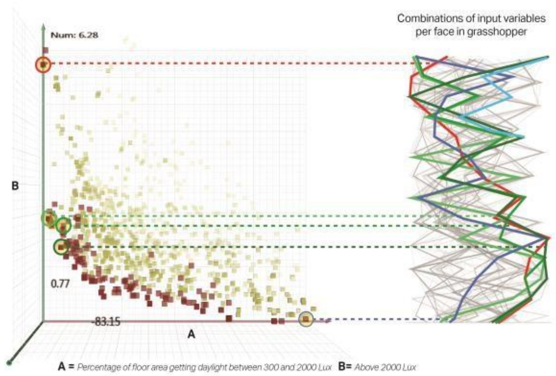

Figure 3: Experiment A Solution Space Visualization

Since the MOO process was setup to search only 1000 total iterations for this experiment, the optimum solutions lie near the many local extrema, as opposed to one global solution. All these local optimum solutions lie approximately on the pareto front where the distance from the origin to these points is minimum. The top three results were manually selected and checked for reasonability before proceeding with the design process.

Experiment A: Limitations

The objectives only focus on daylighting and do not consider any other aspects critical for a high-performance building design such as the HVAC system. Various other aspects need to be considered in practice to ensure the integration of factors such as human comfort, energy performance, and construction cost in the building design. Other objectives that could be evaluated in this type of experiment include:

- Daylight/visual comfort
- Thermal comfort
- Indoor air quality
- Energy consumption v/s cost
- Construction costs
- Embodied carbon

In addition, the extent of the simulation conducted in Experiment A was limited by the capabilities of the software used, i.e. Grasshopper, DIVA, and Octopus. These software are largely focused on the architectural aspects of the building design are not readily compatible with design variables and objectives from other domains.

Experiment B: Objective

The goal of Experiment B was to build upon Experiment A and include the EUI as a third objective employing Honeybee software. This was achieved by incorporating HVAC system types as a new variable. In addition, the exterior wall R-Value was also setup to be an input.

The third objective for this experiment was:

C. To minimize the site normalized energy use intensity (EUI) for the selected zone

Experiment B: Setup

The primary difference in setup from Experiment A was that instead of DIVA, the daylight and energy performance calculations were carried out using Honeybee. Octopus was again used as the MOO solver. To reduce simulation time, the optimization only focused on a single zone in the same test building.

Two additional variables were added in addition to the ones in Experiment A: The glazing type and HVAC systems (Table 2 and Table 3).

Table 2: Two Glazing Types

GLAZING	U VALUE	TVIS	SHGC
Type A	0.16	0.49	0.4
Type B	0.29	0.68	0.4

Table 3: Two System Types

HVAC	DESCRIPTION
System A	Variable Air Volume (VAV) boxes with reheat
System B	Fan Coil Units (FCU) with a separate Dedicated Outside Air System (DOAS)

Experiment B: Outcomes

The experiment resulted in a 3-dimensional solution space showing a pareto frontier of co-optimized solutions (Figure 5). Similar to Experiment A, a limited set of solutions were evaluated based on the parameters in Table 2 and Table 3 and Grasshopper was used to visualize the results.

As an additional step from Experiment A, the solutions were sorted and filtered, based on designer's priorities and logical reasoning, before selecting two optimal and two extreme solutions, as shown in Figure 4.

Two important trends were observed in the solution data (Figure 4): first, starting with the second generation of solutions, the simulations no longer used System A; second, from the eighth generation onwards, the R-value variable did not change. hese trends were probably observed because the HVAC system type and the exterior wall R-value only impact the EUI minimization objective, and the process systematically eliminated values which consistently resulted in a higher EUI. From this point onwards, octopus 'fixed' these two variables and focused on optimizing the remainder.

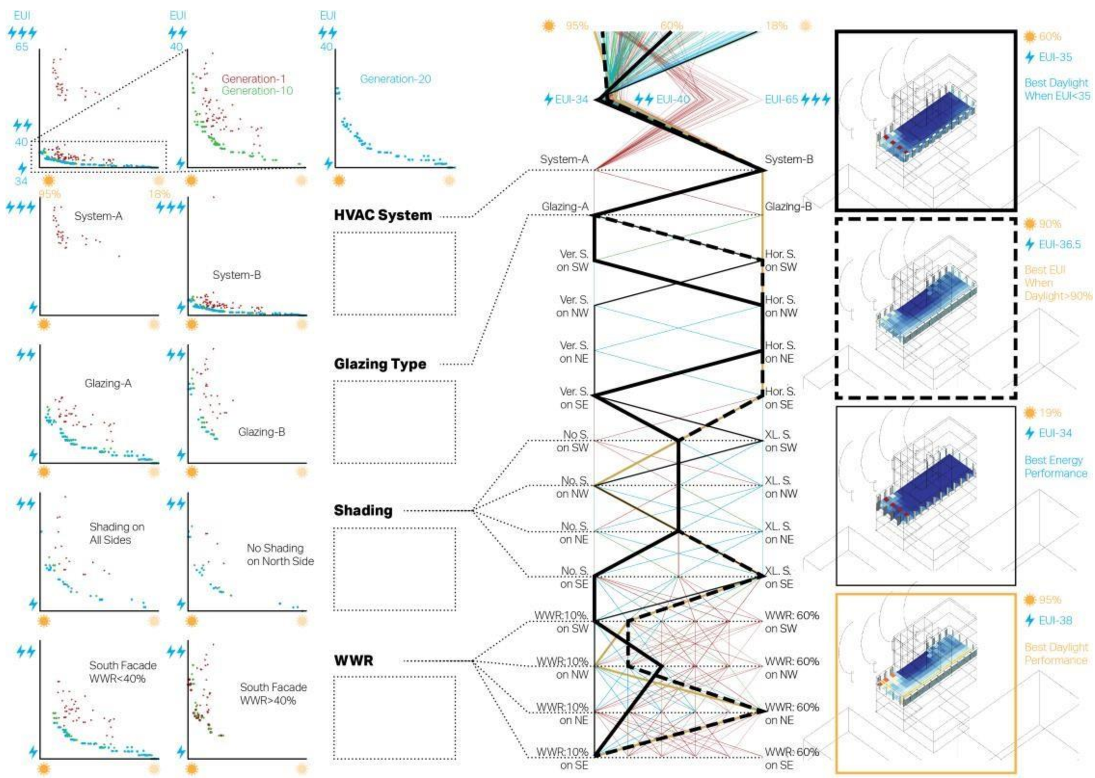

Figure 4: Experiment B Solutions

Experiment B: Limitations

While this experiment considered variables and objectives that are not traditionally paired, resulting in interesting outcomes, it presented several limitations. First, only the factors modeled will be evaluated to achieve the desired outcome. Hence it is up to the user to input all variables carefully and isolate the testing variables. This issue is evident in the bias shown by the results towards certain variables due to the limited scope of the objectives selected. Second, these results were inherently independent of considerations on how the HVAC system type and exterior wall R-value selection impact other project aspects, such as cost.

Another limitation is the additional time required for each simulation. Through test runs, it was observed that additional 3 to 4 minutes per simulation were required to carry out combined energy and daylight calculations for all building's zones. The choice of evaluating only a single zone for this experiment was made to get results in an acceptable time-frame.

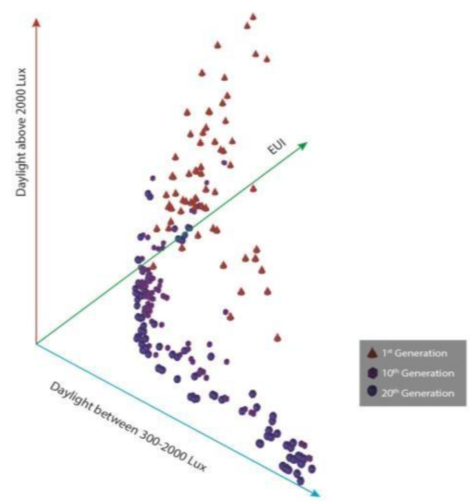

Figure 5: Experiment B 3-D Solution Space

ANALYSIS AND DISCUSSION

The two experiments successfully demonstrated and validated our initial hypothesis that: decision making at early stages of HPB design can be more efficient and reliable with the application of the MOO methodology, hence improving design automation and promoting design collaboration.

Increasing Efficiency

Early stage design process requires rapid decision making due to time constraints when delivering projects, making process efficiency the key to saving time and cost. Employing the methodology outlined enables quick design explorations with one click ahead because customized parametric solutions can be found in a fraction of the time that would be required by a manual process. The 1000 iterations in Experiment B were evaluated in a few hours, something which is impossible to achieve manually.

The increased conversation opportunities for various disciplines also contribute to achieving greater workflow efficiency. Design iterations can be filtered and sorted based on criteria stemming from these conversations. Unfit solutions can be eliminated quickly, saving time - and potentially cost- during the design process.

Increasing Reliability

The traditional design process often produces manually-selected design solutions which “best fit” only from the designer’s point of view, hurting the reliability of the “optimized” results to be able to produce a sustainable and healthy building.

The expanded sample size and the variety of the simulation parameters that can be included in the MOO methodology result in a better chance for reliable design outcomes. Experiments A and B demonstrated that MOO studies in the early-stage design process can reveal significant building design variations and assess the trade-offs between multiple objectives automatically through GA tools. In addition, the second experiment showcased the ability of the methodology to include variables from multiple disciplines (façade design and system selection).

To ensure that MOO simulation outcomes are valuable, all disciplines involved in the design and construction must work together during the early stages to determine the most important design drivers and their inherent parameters and constraints. Stakeholders such as cost estimators, vendors, clients, etc., who are traditionally not part of the design process are also invited to participate. Because of this collaboration, high-quality variables (in the form of constraints) and properly prioritized design objectives can be developed, ensuring that the optimized results are reliable for all parties involved and reducing the need for engineering in later stages of the project.

LIMITATIONS AND FUTURE WORK

It is to be noted that this linear optimization process is highly depended on the outcomes of the previous generation of solutions, which may not always include global optimal solutions. In addition, each experiment's limitations discussed previously provide indications for future work.

Drawing from our discussion, the key limitations are summarized below:

Decentralized Computation

The current computation times are not practical for a simulation to converge on its own at one optimal solution within professional practice conventional timelines. The use of powerful decentralized computation solutions such as cloud-based simulation (Autodesk Green Building Studio) and parallel computing plug-ins (Honeybee Plus for Dynamo) have the potential to speed up the processing. Future testing of the MOO methodology should include tools which are compatible with decentralized computational approaches and compare the results to local computing scenarios.

Integrated Platform

There is still a lack of a more advanced integrated platform where objectives from various domains could be mathematically integrated within the MOO process. As a designer-oriented tool, GH has less opportunities for other disciplines to be involved directly in practices.

BIM-ready platforms, such as Revit, are potential solutions for more collaborative deliveries. Recent tools like Autodesk Refinery provide better avenues to implement the proposed methodology in a BIM-driven workflow. The methodology can then be revised to include different stakeholders. Variables such as cost, buildability, accessibility etc., which are traditionally not part of the early stage design, can be tested using MOO methodology in a set of future experiments.

User-Friendly Tools

The absence of user-friendly tools and the steep learning curve for existing MOO tools are two major hurdles for mass-adoption of this methodology. GH facilitates state-of-the-art energy and daylight analysis by high performance designers with only limited scripting knowledge on, but advanced coding knowledge is still required to bring other metrics on a common platform.

As an alternative approach, the simulation interface can be de-coupled from the sorting and visualization interface. The results can then be sorted and visualized by using certain web-based optimization tools like Design Explorer and Cove Tool, enabling the whole project team to meaningfully use multi-dimensional parametric studies with some degree of ease.

CONCLUSION

A multi-objective optimization process in the early stages of design can improve the workflow efficiency by:

A) Reducing decision-making time and

B) Increasing collaboration between disciplines.

As demonstrated by the experiments, the process enables a potentially exhaustive exploration of design solutions in a fraction of the time and with greater accuracy. MOO methodology can also be utilized to find solutions for broader and seemingly unrelated problems, such as the tradeoffs between human comfort, energy consumption, capital cost, EUI, lifecycle costs etc.

Finally, the ongoing development of integrated optimization software, de-centralized computing technologies and post-optimization sorting tools, coupled with the benefits of a MOO approach in professional practice, make this an important area for future work and knowledge advancement.

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