ITcon
www.itcon.org - Journal of Information Technology in Construction - ISSN 1874-4753

DESIGN SPACE CONSTRUCTION: A FRAMEWORK TO SUPPORT COLLABORATIVE, PARAMETRIC DECISION MAKING

SUBMITTED: July 2017
REVISED: June 2018
PUBLISHED: June 2018 at http://www.itcon.org/2018/8
EDITOR: Kumar B.

John Haymaker, *AIA, PhD*
Director of Research, Director of Process Lab, Perkins+Will;
john.haymaker@perkinswill.com

Marcelo Bernal, *PhD, Senior Researcher & Computational Designer, Assistant Professor*
Perkins+Will; Department of Architecture, Universidad Técnica Federico Santa María;

Marionyt Tyrone Marshall, *AIA, Senior Researcher, Co-Director Energy Lab, Perkins+Will*

Victor Okhoya, *Assoc. AIA, Senior Researcher, Design Applications Manager; PhD Candidate*
Perkins+Will; School of Architecture, Carnegie Mellon University

Anton Szilasi, *Researcher, Perkins+Will*

Roya Rezaee, *PhD, CPHC, Research Scientist, Perkins+Will*

Cheney Chen, *PhD, P.Eng., Senior Sustainable Building + Energy Engineer, Perkins+Will*

Andrew Salveson, *Software Engineer, Perkins+Will*

Justin Brechtel, *Senior Computational Designer, Perkins+Will*

Luc Deckinga, *Digital Practice Manager, Perkins+Will*

Hakim Hasan, *Researcher, Perkins+Will*

Phillip Ewing, *Researcher, Perkins+Will*

Benjamin Welle, *PhD, PE, BD+C, BEMP, Director of Energy Lab, Perkins+Will*

SUMMARY*: This paper describes a framework of concepts and processes that support teams to construct and explore design spaces maximizing social, environmental, and economic value. The framework guides teams through processes of problem formulation, alternative generation, impact analysis, and value assessment. The paper describes an extensible supporting computational infrastructure based on a system integration approach and structured in four layers: parametric user interface, analysis engines, software interfaces, and data visualization. The paper describes implemented functionality in terms of goal and preference-setting, parametric modeling, energy, daylight, view, first cost, lifecycle cost and lifecycle carbon, and demonstrates application through a test case. The paper concludes with evidence about the power and flexibility of the DSC framework with the results of a professional case study, and a survey of professional and student architects who have been trained in constructing and exploring parametric, performance-based design spaces.*

KEYWORDS: *design space, problem formulation, parametric modeling, performance, value, decision making*

REFERENCE: *John Haymaker, Marcelo Bernal, Marionyt Tyrone Marshall, Victor Okhoya, Anton Szilasi, Roya Rezaee, Cheney Chen, Andrew Salveson, Justin Brechtel, Luc Deckinga, Hakim Hasan, Phillip Ewing, Benjamin Welle (2018). Design space construction: a framework to support collaborative, parametric decision making. Journal of Information Technology in Construction (ITcon), Vol. 23, pg. 157-178, http://www.itcon.org/2018/8*

1. INTRODUCTION

Design is a decision-making process. It is about the questions we ask and the decisions we make. Performance-based design specifically seeks to maximize the value of those decisions. To make decisions with confidence, multidisciplinary teams need to gather, weigh, and document rationale efficiently. Design literature generally recommends exploring the broadest range of alternatives for the widest range of experiential, ecological and economic factors (Hueting, 1990) possible, within project time and budget constraints. For example, experiential factors may include the aesthetics, thermal comfort, and views afforded by an architectural space. Environmental factors may include how much energy or water the structure consumes through its life cycle. Economic factors may include how much it costs to construct and operate. Different alternatives for the same design problem may perform better or worse on each factor, and different stakeholders may have different priorities over these objectives. Design teams must somehow engage project stakeholders, understand goals and preferences, generate and analyze alternatives, and make and communicate decisions that maximize value.

The general issue is that decision making in practice is a complex process that requires the appropriate input of many stakeholders and experts, and the collection and synthesis of much rationale. Under standard project deadlines and budgets, design decisions are poorly defined, constructed and explored, and value is not maximized (Haymaker, Chachere, & Senescu, 2011). In fact, many design decisions are based on heuristics and assumptions derived from professional experience rather than exhaustive analyses (Cross, 2004; Lawson & Dorst, 2009). A design problem is a set of design parameters, each with a range of possible choices. A design space is the cross product of all the parameter spaces of the problem (Zdrahal & Motta, 1995). Clevenger & Haymaker (2011) elaborate this definition to include Objective, Alternative, Impact, and Value parameter Spaces.

New parametric and performance-based design tools are emerging that promise to allow design teams to construct and explore better design spaces, faster, and get feedback from their initial intuitions (Flager, Welle, Bansal, Soremekun, & Haymaker, 2009; Geyer, 2009; Sanguinetti, Bernal, El-Khaldi, & Erwin, 2010; Lin & Gerber, 2014). However, to effectively apply these methods in practice, design teams require a unified framework of concepts, processes, and tools to guide them in collaboratively constructing and exploring design spaces.

Frameworks to assist teams with constructing and exploring design spaces do exist. Design Thinking is a framework of concepts that helps teams through iterative phases of inspiration, ideation, and implementation, with several sub processes to guide teams through these phases (Rowe, 1987; Cross et al, 1992; Brown, 2008). However, these methods are focused on creative problem formulation and solving, and lack a computational focus to guide teams in the implementation of computational processes to support them in these phases. Model-based systems engineering is another framework for designing, documenting and implementing systems. However MBSE frameworks are comprehensive for designing and detailing in great complexity, and do not focus specifically on constructing and exploring design spaces, particularly for AEC problems. While the work presented in this paper are informed by and build on this prior work, it is also motivated by the lack of a framework which has been develop for teams to construct and explore AEC design spaces.

This paper therefore asks two interrelated questions: What is a framework that can enable AEC design teams to leverage parametric design technologies to construct and explore design spaces? How might this framework impact the construction and exploration of these design spaces? We address these questions through iterative development and validation (Hartmann, Fischer, & Haymaker, 2009) through its application in professional projects and university classes.

The next section describes the Design Space Construction (DSC) framework. Synthesized from concepts in design and decision theory, the DSC framework guides teams through a process of *Problem Formulation* - where decision makers assemble teams and establish objectives and process; *Alternative Generation* - where designers create a space of options; *Impact Assessment* - where experts understand, environmental, and economic performance; and *Value Assessment* - where decision makers weigh priorities and information certainties, and make and communicate decisions.

The following section explains the framework and implementation through a test case – the specification of design parameters for a re-locatable classroom layout, and its optimization for energy, daylight, view, costs, and carbon emissions considerations. We demonstrate the benefits of the DSC framework with results of a professional case study – the design of an academic building facade. We describe how a design team using the DSC framework was able to more systematically and accurately maximize value compared to the results of three other design teams who addressed the same problem using traditional methods. A survey of sixteen professional and graduate student architects who have been trained in the DSC framework demonstrates that it can enable more efficient and effective design space construction and exploration than current practice.

2. FRAMEWORK FOR DESIGN DECISION MAKING

Decision-making is a process of gathering and structuring information to support and make decisions. It includes clarifying the organization of the participants and their roles, defining objectives, generating alternatives, evaluating performance and assessing value. The presented framework (Fig. 1) synthesizes definitions of the relevant concepts and processes involved in the construction of a design space to support decision-making (Clevenger & Haymaker, 2011; Haymaker et al., 2011; Parrish & Tommelein, 2009).

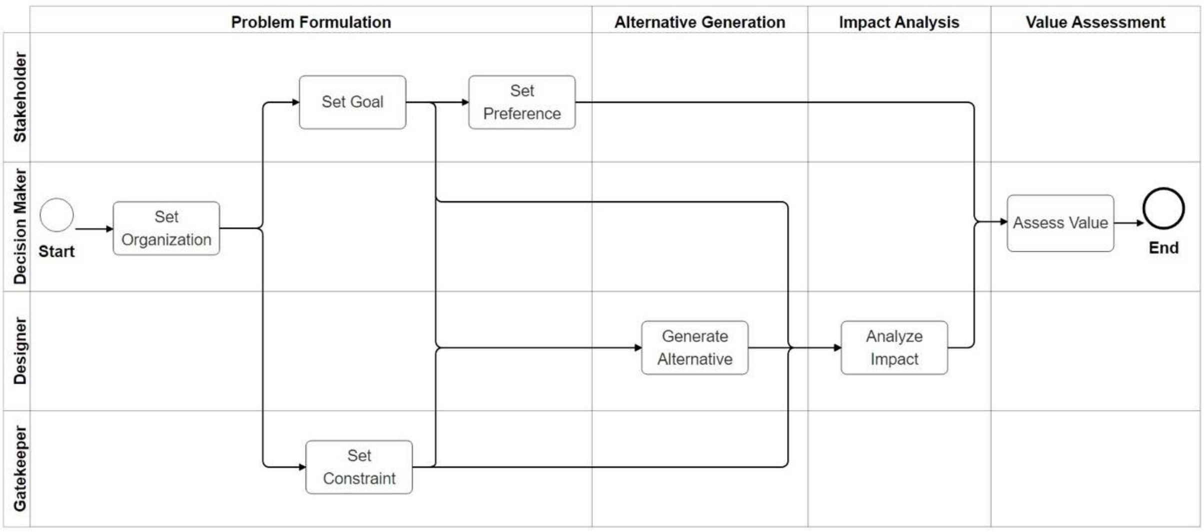

FIG. 1: The Design Space Construction Framework: describing the activities and interaction among participants. While the diagram indicates a start and end-point, the processes are iterative.

2.1 Problem formulation

Problem formulation assembles the relevant organization, and establishes the objectives. A decision requires many types of expertise, and the organization represents the participants and their roles in the decision-making process. Participants may be affected by the decisions, define objectives, apply constraints, generate or analyze alternatives, or make the decisions. We identify four major roles: *stakeholders* are types of people affected by the decision, *gatekeepers* have the ability to define constraints, *designers* help generate alternatives and measure impacts of alternatives on objectives, and *decision makers* appoint stakeholders and designers and then weigh value to make decisions. The interaction among these participants defines the high-level model of the decision formulation process.

Objectives are specific targets to achieve or failures to prevent (Becker, 2008). In other words, they can be either a desirable goal or a mandatory constraint. *Goals,* defined by *stakeholders*, represent specific experiential, ecological, or economic targets. However, in most cases, it is impossible to maximize all goals simultaneously; the optimization of a single goal compromises the ability to maximize overall value, and trade-offs can emerge. *Constraints*, defined by *gatekeepers*, represent the admissible limit of an input variable or outcome and must be satisfied for an *alternative* to be viable. The declaration of *metrics* allows the verification of fulfilment of the *constraints*, and the assessment of the degree of satisfaction of the *goals*.

Preferences express the *stakeholders'* priorities. Decision-makers can sort properly defined objectives in order of importance, from those that are mandatory to those that are merely desirable. Gathering *preferences* can help drive the formulation, generation, and analysis when compromises must occur. Ultimately, a set of *design alternatives* may rank differently depending on the set of *preferences* used for evaluation.

2.2 Alternative generation

Alternatives are the explored potential solutions to a given design problem. Each of those *alternatives* corresponds to a particular set of *options* for every *variable* of the problem. *Variables* can be discreet or continuous input parameters within a *range* that constrain all possible states of such a *variable* between lower and upper bounds (Fig. 2). *Designers* generate *alternatives* by changing *options* of *variables* of the geometry or the attributes. Since the size of the space of alternatives is the product of all the possible combinations of *options*, the team must rationalize the *ranges* of the *variables* and the number of *options* to efficiently explore the *design space*.

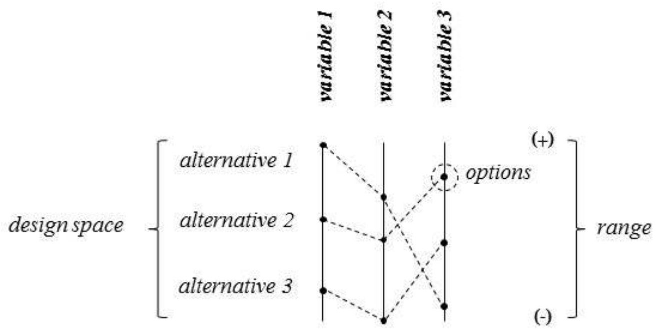

FIG. 2: Sample of three alternatives of the design space.

2.3 Impact analysis

Impacts are the amount of influence the combined *options* of an *alternative* have on the performance of each experiential, ecological, and economic objective (Fig. 3). Net performance of an *alternative* relative to these objectives is not enough to determine its advantages and overall *value* (Suhr, 1999). The decision maker needs to standardize the individual *impact* values to enable a rational comparison of choices. Designers may include quantifications of uncertainty in this step, although we omitted quantifications of uncertainty from this discussion for simplicity.

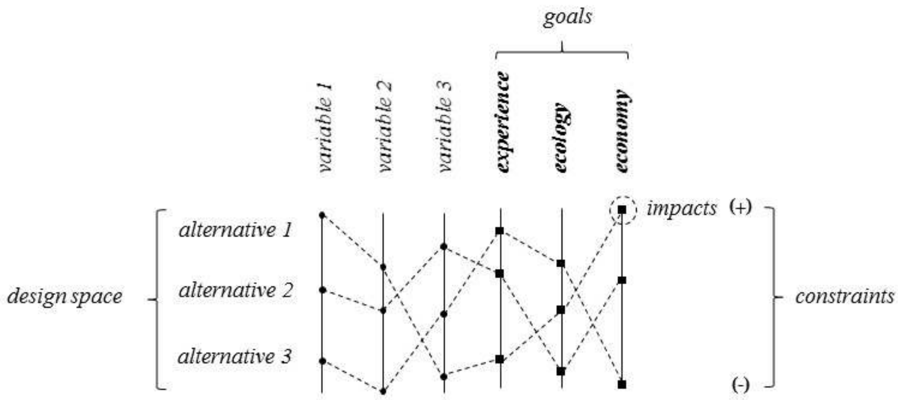

FIG. 3: Visualization of impacts.

2.4 Value assessment

Value is a synthesis of alternative *impacts* and *stakeholder* preferences into an objective function that orders the *alternatives* (Hazelrigg, 1998) (Fig 4). Depending on the certainty of information and *preferences of stakeholders*, different *alternatives* can score the highest value (Arrow, 1971). Value in this framework is defined broadly to encapsulate both multi-attribute utility (Keeney & Raiffa, 1993) and economic (Collopy & Collopy, 1997) objective functions.

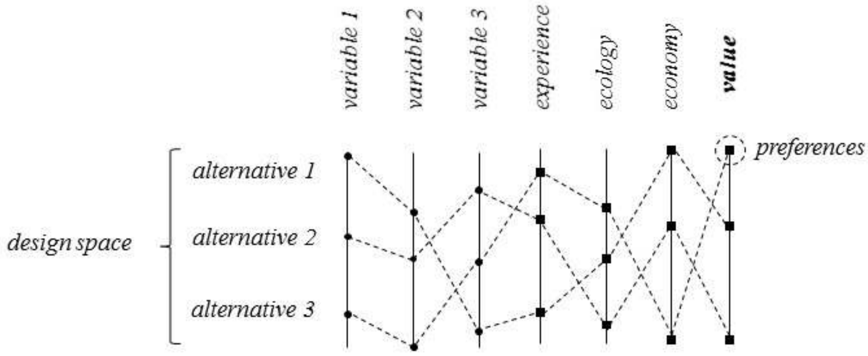

FIG. 4: Value synthetizing preferences.

The formulation of a *value* function is usually an iterative process of narrowing and expanding the search as *decision makers, stakeholders*, and *designers* learn more about the *design space* and their *preferences*. The process of sorting and prioritizing *design alternatives* can include ordering of alternatives according to their performance on each objective; on value for each stakeholder; or for all stakeholders. Figures 1-4 derive a common and useful method of visualizing all of the Design Space information in a Parallel Coordinates Plot (PCP) chart (Inselberg, 1997). Other methods of visualization, such as scatter plots, sensitivity charts and others are also useful, but this paper uses PCPs as the principal method for visualizing and exploring design space data.

3. PROCESS IMPLEMENTATION

Prior efforts at multi-criteria design and optimization (Flager et al., 2009) have integrated problem formulation, alternative generation, impact analysis, and value assessment into design systems. However, these efforts lacked a pre-defined framework of concepts, processes, and tools that enabled a design team to construct and explore a new design space efficiently and effectively. This paper contributes the synthesis of the conceptual framework described above with an extensible computational infrastructure based on a systems integration approach (Bernal, 2016; Reichwein & Paredis, 2011). This infrastructure includes visual parametric modeling technology for automation of alternatives generation and performance analysis, and web-based resources that selectively upload and share data across systems. This infrastructure helps teams organize and define the objectives, analyses, ranges for every design variable, and automates the generation, analysis and data visualization of the design space. The implementation has four layers to address the challenge of data flow across parametric models, analysis software and web-based services (Fig. 5).

A *parametric modeling layer* supports the design generation and analysis specification tasks. The *analysis engines layer* executes the actual performance analyses. The *interface layer* extracts the input data required by the analysis engines from the parametric models and collects the results. The *data visualization* layer gathers stakeholder input preferences and plots the data of every *alternative* of the *design space*.

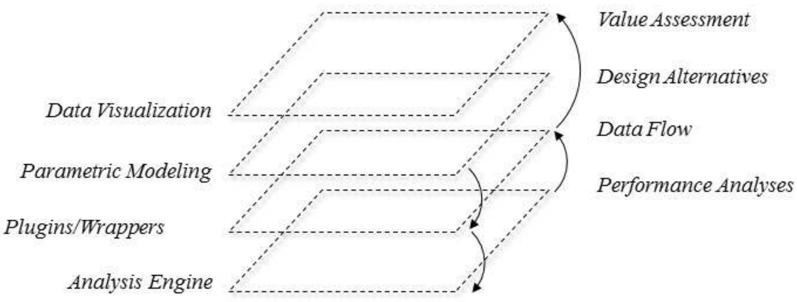

FIG. 5: Layers of the computational infrastructure.

3.1 Parametric modeling

The parametric modeling layer is implemented using well-known visual programming tools (i.e. Grasshopper & Dynamo) for geometric representation and automation of the generation of the design alternatives (Turrin, von Buelow, & Stouffs, 2011). Geometric variations of the same configuration allow exploring different combinations of input parameters. This layer also derives the geometric features and attributes, also called analytical input models, required for each analysis. For this purpose, the population of *alternatives* decomposes into building components, material attributes, and derived parameters.

3.2 Analysis engines

The analysis layer represents all the required software for the performance analysis. The current workflow requires analysis engines for Energy and Daylight. Other analyses, such as cost, are done in the context of the parametric modeling environment because they are computationally trivial.

Energy simulations are based on the EnergyPlus engine (EnergyPlus, 2016) that requires analytical input models representing thermal zones, related attributes, and weather data to calculate the temperature inside each room for every hour of the year, in order to estimate the total energy use, in kWh. The additional OpenStudio software (OpenStudio, 2016) facilitates the process by exporting the zones and their attributes to EnergyPlus, producing reports of inputs and outputs, and keeping track of the EnergyPlus IDF files.

Daylight simulations rely on the DAYSIM engine (DAYSIM, 2016) based on Radiance (Radiance, 2016) which undertakes the calculations using the envelope geometry and the material properties. The process simulates rays representing light bouncing within the space and creates a grid of test points a certain height above the floor to register and plot the daylight level at each point.

3.3 Interface

The interface layer gathers plugins that interface between the design alternatives derived from the parametric model and the analysis engines. Interfaces do not execute the analyses, rather they input the data from the analytical input models required by the analysis engines. These plugins also collect and publish the results of the analyses for further post processing and visualization.

The Honeybee & Ladybug (HoneyBee & Ladybug., 2016) plugins provide components to interface with Open Studio, EnergyPlus, DAYSIM and Radiance within the parametric modeling environment by importing the necessary weather files, and collecting and formatting the geometry and attributes for the exchanges (Sadeghipour Roudsari & Park, 2013). This interface allows running the computations in the background out of the parametric modeling session in order to improve the stability and speed of the process while processing large populations of alternatives.

3.4 Data visualization

The *data visualization* layer supports data interpretation. The technique represents information as a data table. The data set integrates and associates in the same row input parameters and performance *impacts* from the same design alternative. Data visualizations help sort the data of every column from maximum to minimum from top to bottom and relate each row of data to generate PCP charts for visualization of multidimensional data that facilitate the exploration of trade-offs across the indicators for decision making.

The results of the impact analyses and the parameters for every alternative can be exported in real time via a web-based system that uses JSON files for data exchange (Flux, 2016) to online spreadsheets that post-process the data. These results are either standardized for normally distributed data or normalized, then weighed, and sorted by a value function that rationalizes and synthesizes the *stakeholder objectives* and *preferences*. Finally, a custom web-based engine for visualization takes in the outcome parameters, impacts and value from the spread sheet to generate the interactive plot.

4. TEST CASE

This section presents a test case to demonstrate how to apply the framework. Sprout Space is a flexible, modular, mobile classroom (Fig. 6) that creates a healthy environment for different learning styles (Post, Allen, Harrison, & Turckes, 2017). Embodied within Sprout Space are several architectural decisions about configuration and materiality that will have an impact on the experience, ecology, and economics of the project. For the purpose of this study, we assume a site located in Los Angeles, CA, Climate Zone 3 according to ASHRAE 90.1 (ASHRAE, 2013). The challenge is to position one Sprout Space structure on the site so as to maximize the value to the *stakeholders*.

FIG. 6: Sprout Space

4.1 Project goals

The decision makers define the team and roles such as stakeholders representing the administrators or maintenance people; designers including architects, mechanical engineers, and contractors; and gatekeepers including city building officials and school policy makers. The stakeholders' primary *goals* driving the project for this case study are minimizing some indicators such as energy use, maximizing others, for instance, daylight, or providing a view from inside to outside, as well as specifically to a couple of landmarks on the site. Table 1 shows the indicators, *metrics,* and one *stakeholder*'s *preferences* for Energy Usage, Daylight, Quality View, Direct Line of Sight, First Cost, Utility Cost, and Life Cycle Cost, and Carbon Dioxide Emission analyses.

TABLE 1: Sprout Space objectives, metrics and weight of preferences.

Objective	***Indicator***	***Metric***	***Preference***
Minimize Energy Use	Energy Use (EU)	kWh	20%
Maximize Daylight	Daylight Factor (DF)	%(lx/m2)	10%
Maximize View	Quality View (QV)	% (m2)	10%
Provide View	Direct Line of Sight (DLS)	% (m2)	10%
Minimize the First Cost	First Cost (FC)	USD	10%
Minimize Utility Cost	Utility Cost (UC)	USD	10%
Minimize Life Cycle Cost	Life Cycle Cost (LCC)	USD	20%
Minimize Carbon Dioxide Emission Rate	CO_2 Output Emission Rate (CDE)	Metric Tons CO_2	10%
			100%

4.2 Design space

The designers discuss the options and range of variations on the Sprout Space alternatives they wish to explore. The options include the orientation of the structure, the displacement of the two rectangular plans to each other, the angle of the inverted roof, and the dimensions and material properties of design features including windows, sunshades, and clerestory windows, and doors (Fig. 7).

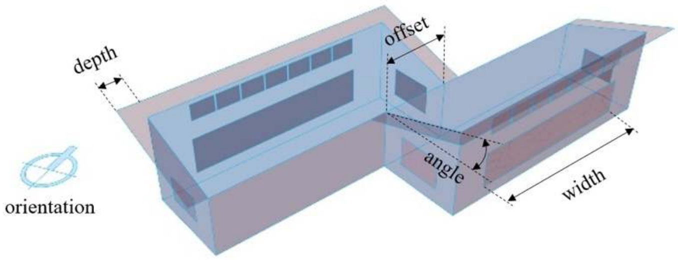

FIG. 7: Geometric variables to explore.

As the discussions progress and the team faces trade-offs between process efficiency and breadth of exploration, they narrow their exploration to some of these variables while making assumptions derived from the regulations and best practices for other variables. Figure 7 shows five geometric *variables* to explore, their *units* and realistic *ranges* (Table 2), and four different optional constructions types: Glass Fiber Reinforced Concrete (GFRC), Structurally Insulated Panel (SIP), Cross Laminated Timber (CLT) and Precast Concrete Panel (PCCP). In the last column, the table shows the number of *options* of every *variable* for this case study that, combined, produce 1296 design alternatives. A designer then develops a parametric model of Sprout Space capable of generating these alternatives (Fig. 8).

TABLE 2: Sprout space investigated variables.

Variable	***Unit***	***Range***	***Options***
Classroom Offset	feet	0 - 60	3
Classroom Orientation	degree	0-360°	6
Window Width	feet	1 - 9	3
Roof Angle	degree	0 - 10	2
Overhang Depth	feet	0 - 3	4
Constructions	-	PCCP, SIP, CLT, GFRC	4

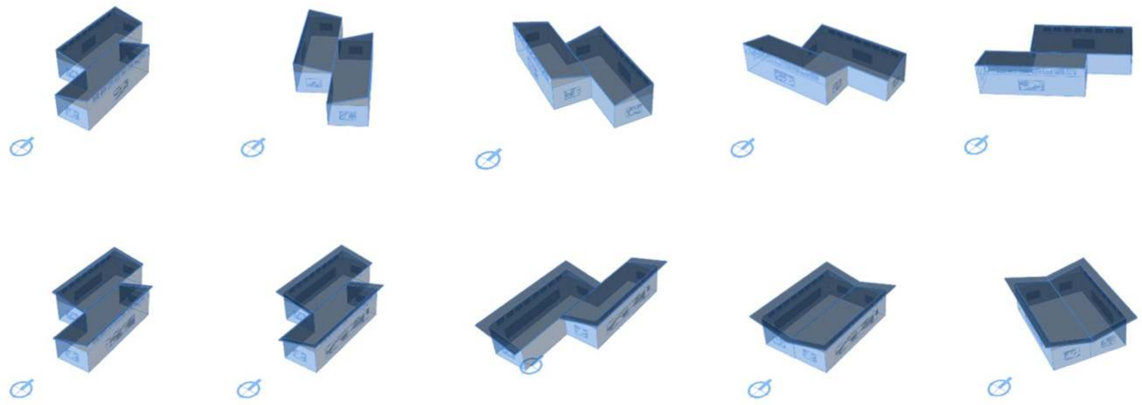

FIG. 8: A Sample of 10 of the 1296 alternatives.

4.3 Performance analyses

Once stakeholders define objectives and designers generate the alternatives, the next step is to determine the performance *impact* of each alternative on each objective (Fig. 9). The designers configure both previously defined and newly developed components from the technical implementation described above to enable performance analyses according to the objectives. Together, simulations of 1296 design iteration using the implementations for daylight, energy, view, first, utility and lifecycle cost and carbon takes about 16 hours to execute on a laptop with an Intel Processor Coe i7 s. This extensible infrastructure can integrate additional analyses for other objectives beyond those described in this paper. Parallelization and other strategies for managing design space size are discussed in upcoming papers.

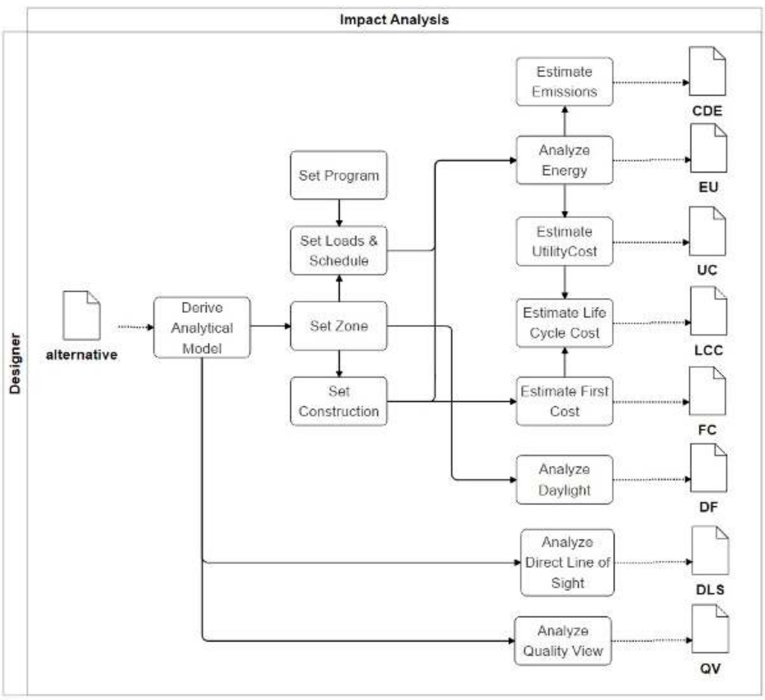

FIG. 9: Extension of the analyze impact action.

4.3.1 Energy consumption

An energy simulation calculates the heating and cooling energy required to keep the building at a comfortable temperature between 19 and 26C° throughout the year. Before running a simulation, the parametric model derives an analytical input model that converts the building mass into zones, describing the amount of lighting, occupancy schedules, internal loads, and equipment in each zone according to the specifications for the climatic zone in ASHRAE standards (Table 3). It also defines the adjacency types between zones, and material properties and overhangs of the envelope.

TABLE 3: Assumptions for Sprout Space case study.

variable	***SI units***	***option***
Air Changes Per Hour	ACH	0.6
Ventilation Rate per Area	m^3/ m^2s	0.0006
Ventilation Rate per Person	m^3/ m^2s	0.005
Number of People per Area		0.2499
Lighting Power Density	W/ m^2	9.3650
Occupancy Schedule		daily
Equipment Loads per Area	W/ m^2	10.9792
HVAC heating set point in Celsius	°C	18
HVAC cooling set point in Celsius	°C	26
HVAC heating setback setpoint in Celsius	°C	12
HVAC cooling setback setpoint in Celsius	°C	32
Baseline HVAC System		hybrid system

TABLE 4: Thermal properties of climate zone 3B based on ASHRAE 90.1-2013.

Properties	***SI Units***	***Option***
Utility Rate	Real	0.1274
Roof R-value	m^2K/W	4.4057
Envelope Solar Reflectance	Real	0.7
Envelope Thermal Emittance	Real	0.9
Envelope Visual Absorptance	Real	0.7
GFRC Walls R-value	m^2K/W	2.2887
SIP Walls R-value	m^2K/W	2.2910
CLT Walls R-value	m^2K/W	1.3393
PCCP Walls R-value	m^2K/W	2.2887
Floor R-value	m^2K/W	0.2414
Glazing U-value	W/m^2K	2.8372
Glazing SHGC	Real	0.250
Glass min Visual Transmittance (min VLT)	Real	0.275
Ceiling Surface Reflectance	Real	0.800
Interior Wall Surface Reflectance	Real	0.500
Floor Surface Reflectance	Real	0.200
CO2 Total Emission Rate (Non-baseload)	Real	0.00025791241

4.3.2 Daylight

A daylight simulation calculates the daylighting quantity and quality within the spaces of the building. The design team chose to calculate the Daylight Factor (DF) - the ratio between the interior and exterior illuminance levels of natural lighting. The algorithm calculates DF under a CIE overcast sky model that represents the worst-case scenario assuming a 100% cloudy sky and does not take into account the direct sunlight. Therefore, the orientation of the building does not affect the results of the calculations. Even though it is a simplistic calculation of the quality of the natural lighting within the spaces, it provides a preliminary evaluation to support early design decisions. For example, a DF of five means that 5% of the daylight from outside has made it in the space. A DF of less than two implies a requirement for the use of artificial lighting, between two and five, artificial lighting may be needed part of the time, and over five artificial lighting not required, but glare and solar gain may begin to cause problems. Figure 10 shows heat maps for ten different alternatives. Blue areas represent comfortable DF, while yellow and red areas are out of acceptable range.

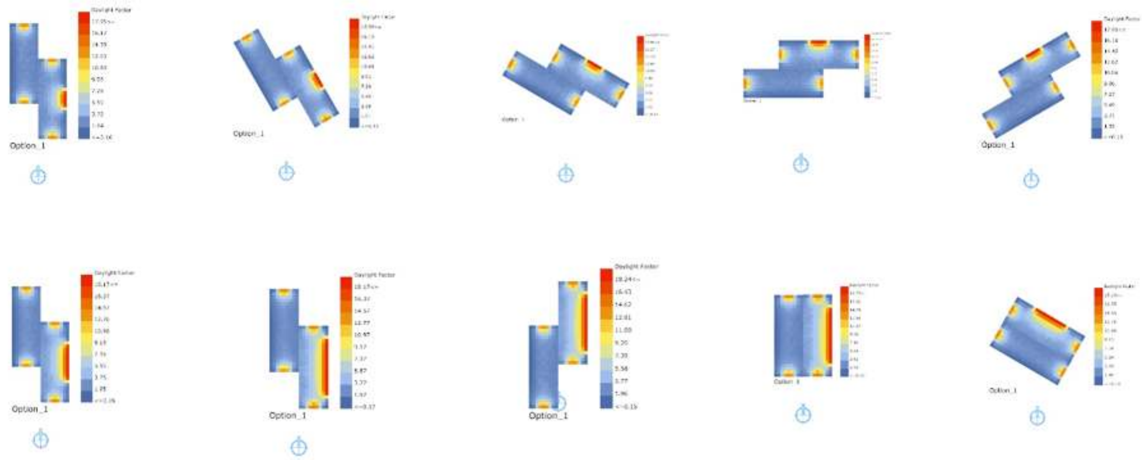

FIG. 10: A sample of 10 of the 1296 alternatives evaluated for DF.

4.3.3 View quality

The purpose of the *view quality* analysis is to assure a visual connection with the outdoor environment. The designers choose to explore two measures for view quality. Direct Line of Sight (DLS) calculates the percentage of the floor area of the building with an exterior view by calculating the maximum view angle from the windows to derive the dark areas (Figure 11), which are dependent on the dimensions of the room, the thickness of the wall, and the size of the window.

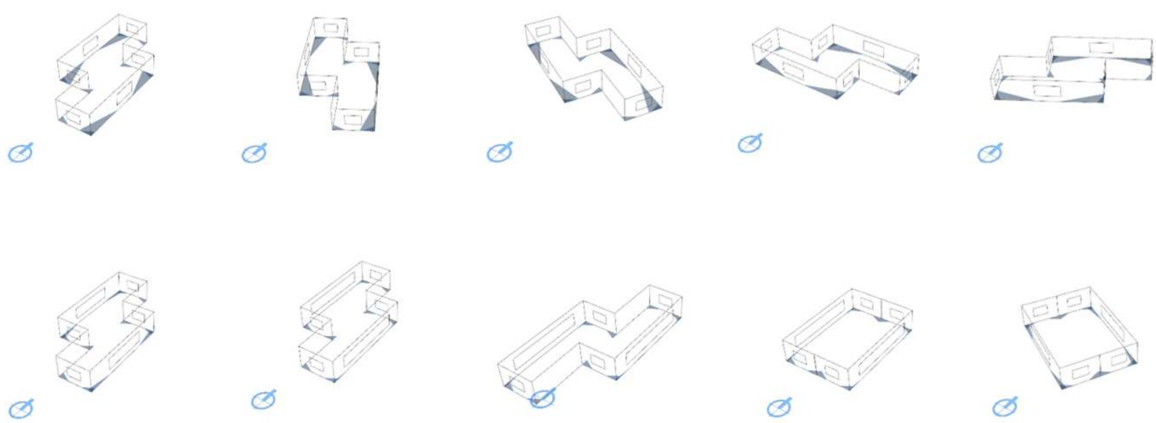

FIG. 11: A sample of 10 of the 1296 alternatives evaluated for DLS.

The Quality View (QV) indicator calculates the percentage of the area that allows the view of some essential elements of the landscape. QV projects a view cone perpendicular to the window plane, and every time it intersects the target, it counts the area of the viewpoint. These two indicators are based on the Indoor Environmental Quality Chapter from the Guide for Building Design and Construction LEED V4 (Council, 2016). Unlike the previous analytical input models, the model required by these two analyses only takes in geometric features, and the calculation runs in the parametric modeling environment without any interfacing with another tool.

4.3.4 First cost

First cost estimation comprises three major items: Substructure that includes foundation, slab on grade and excavation; superstructure including floor, roof, exterior walls, glazing, doors, roof covering, and drainage construction; and interiors that include partitions, floor and ceiling finishes, and fittings. The designers' analysis in this case study focused on the envelope, considering the designed floor area, choice of the opaque walls, and the doors, interior partitions, transparent glazing and roof surface areas from four predefined typical options of constructions (GFRC, SIP, CLT, and PCCP) based on national average construction cost data (RSMeans, 2017).

4.3.5 Utility cost

The utility cost is the product of the commercial electricity rate of 0.1274 for the city of Los Angeles (Local, 2017) and the total building energy usage, based on the simulation data. The model does not include a portion of the building energy use for natural gas.

4.3.6 Life cycle cost

The life cycle cost indicator evaluates the First Cost of the construction, but also includes the mechanical systems periodic replacement, operating and maintenance, utility cost with escalation for rising annual prices, insurance, property taxes, replacement expenses, and depreciation tax. For this exercise, the LCC simply calculates the sum of the First Cost and the Utility Cost with an escalation rate of 3% for thirty years.

4.3.7 Carbon dioxide emissions

CO2 emissions vary depending on the geographic region for electricity, other fossil fuels, and natural gas (Rothschild & Pechan, 2009). The calculation for CO2 emissions provides an indication of the performance of each alternative regarding its expected emission factor, in the Los Angeles region. The energy demand in kWh is multiplied by the CO2 Emission Rate for the individual sub-region according to the Emissions & Generation Resource Integrated Database (eGRID) EPA reports for non-baseload CO2 output emission rates from the year 2015. Non-baseload emission refers to those plants that supply electricity, combust fuel, and high capacity factors less than 0.8. The assumption for non-baseload emission excludes capacity factors over 0.8 for a better prediction of emission reductions. The factor for the CO2 Output Emission calculation uses a sum of the non-baseload emissions divided by the sum of non-baseload net generation, divided by a unit conversion factor for the rates.

4.4 Value

The Sprout Space design challenge has multiple objectives, a significant number of *alternatives*, and some emergent tradeoffs in the *impacts*. For example, increasing the window/wall ratio of the building envelope improves View Quality, but also increases Energy Consumption for heating in the winter or cooling in the summer. After collecting the performance data, the *decision maker* must rationally standardize or normalize, weigh, integrate into a value function, and visualize this information to support *decisions*. The design team chose a relatively straightforward strategy for this case study, described in Figure 12.

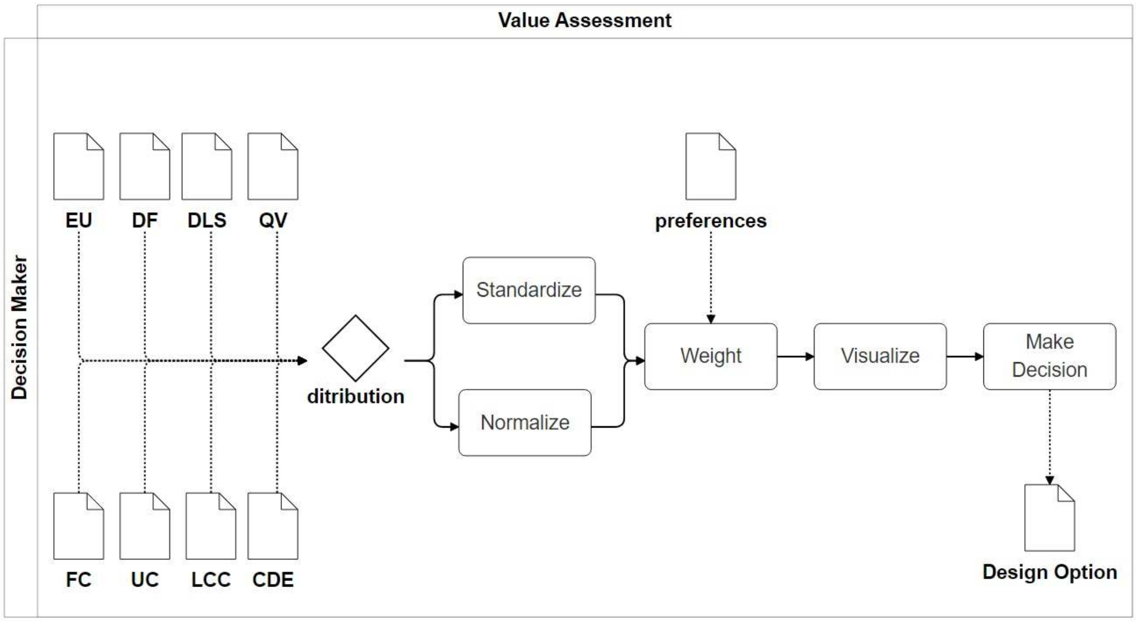

FIG. 12: Extension of the assess value action.

4.4.1 Standardization and normalization

Comparison of the results from the different analyses reveals data that differs in magnitude and units. For example, while the model expresses Energy Use in kWh, the DLS is a percentage of the floor plan area. When results have a normal distribution, decision makers can use data standardization derived from the combination of the multiple inputs. This technique quantifies how far from the mean of one analysis is from any particular result. Zero represents the mean, a positive number reflects results above the average, and negative numbers reflect a result below the average. The standardize function is described by the following expression, where 'z' is the standardized result, '$\varkappa$' is the original result of the analysis, 'μ' the mean of the results, and 'σ' the standard deviation of the entire population (Table 5).

$$z = (\varkappa - \mu) / \sigma$$

This standardization provides valuable feedback for decision makers. However, in many cases, the results do not have a normal distribution. For example, QV based on a true-false evaluation of reaching a target or not. Unlike Energy Use, the average values have no meaning for this indicator.

TABLE 5: Random sample of standardized analysis of 10 alternatives.

Run	*Offset*	*Orient*	*Width*	*Angle*	*Depth*	*Const*	*EU*	*DF*	*DLS*	*QV*	*FC*	*UC*	*LCC*	*CDE*
1	4	0	20	1	0	GFRC	-1.00	-0.57	N/A	N/A	-0.84	1.00	-0.30	1.00
138	12	240	10	1	5	GFRC	-1.63	-1.68	N/A	N/A	-0.73	1.63	0.05	1.63
212	12	240	30	9	5	GFRC	1.77	1.62	N/A	N/A	-2.34	-1.77	-2.65	-1.77
320	20	240	30	9	5	GFRC	1.54	1.62	N/A	N/A	-2.14	-1.54	-2.40	-1.54
426	4	240	10	9	5	SIP	1.54	1.62	N/A	N/A	-2.14	-1.54	-2.40	-1.54
517	12	240	20	9	0	SIP	-1.35	0.55	N/A	N/A	0.13	-1.35	-0.43	-1.35
605	20	180	30	5	5	SIP	0.34	1.12	N/A	N/A	0.13	0.34	0.25	0.34
728	4	120	30	9	0	CLT	-2.48	1.61	N/A	N/A	0.57	-2.48	-0.52	-2.48
801	12	180	10	5	0	CLT	0.34	-1.05	N/A	N/A	1.09	0.34	1.04	0.34
924	20	120	10	5	5	CLT	0.53	-1.05	N/A	N/A	1.25	0.53	1.26	0.53

To address the integration of normal and non-normal distributed results in a value function, we can use an alternative normalization technique that sorts the results from zero, the minimum, to one, the maximum (Table 6). The following expression represents this function, where ‘v’ is the normalized value ‘x’ minus the minimum value from the original results over the maximum value minus the minimum.

$$v = (\varkappa - \min) / (\max - \min)$$

Before assigning weight, again, the Energy Use, First Cost, Utility Cost and Life Cycle Cost invert, since the lower the value, the better the performance. The inversion has the following form, where ‘y’ is the final inverted version of the normalized value ‘v.'

$$y = 1 - v$$

TABLE 6: Random sample of normalized analysis of 10 alternatives.

Run	***Offset***	***Orient***	***Width***	***Angle***	***Depth***	***Const***	***EU***	***DF***	***DLS***	***QV***	***FC***	***UC***	***LCC***	***CDE***
1	4	0	20	1	0	GFRC	0.78	0.33	0.83	0.74	0.41	0.78	0.52	0.78
138	12	240	10	1	5	GFRC	0.91	0.00	0.00	0.00	0.44	0.91	0.59	0.91
212	12	240	30	9	5	GFRC	0.20	1.00	1.00	0.11	0.05	0.20	0.04	0.20
320	20	240	30	9	5	GFRC	0.25	1.00	1.00	0.11	0.10	0.25	0.09	0.25
426	4	240	10	9	5	SIP	0.50	0.34	0.00	0.00	0.60	0.50	0.55	0.50
517	12	240	20	9	0	SIP	0.29	0.67	0.83	0.05	0.64	0.29	0.50	0.29
605	20	180	30	5	5	SIP	0.29	0.67	0.83	0.05	0.64	0.29	0.50	0.29
728	4	120	30	9	0	CLT	0.05	0.99	1.00	0.85	0.75	0.05	0.48	0.05
801	12	180	10	5	0	CLT	0.64	0.19	0.00	0.24	0.87	0.64	0.80	0.64
924	20	120	10	5	5	CLT	0.68	0.19	0.00	0.63	0.91	0.68	0.84	0.68

4.4.2 Weights

Weighting uses the *stakeholder's preferences* declared in Table 1 that define the level of influence that the *impact* of one objective should have in the overall *value*. The next expression represents the weight function, where ‘ω’ is the weighted result of ‘y,' and ‘ρ’ the preferences factor.

$$\omega = y^* \rho$$

4.4.3 Value function

The value is the sum of all the standardized or normalized, weighed, and in some cases inverted, results, where ‘*n*’ is the total number of weighted indicators. Variations in the distribution of the percentage of influence of the *preferences* ‘ρ’ can lead to different alternatives. Table 7 shows a sample evaluation of 10 alternatives that consider the *variables* defined in Table 2 complimented with the corresponding results for every indicator, and subsequently, the weighted normalized *impacts* synthesized in the *value function.* The table highlights *alternative* 605 as the one with maximum *value* scoring 68% according to the *preferences* declared in Table 1.

$$\sum_{i=1}^{n} \omega_i$$

TABLE 7: Random sample of value analysis of 10 alternatives.

Run	*Offset*	*Orient*	*Width*	*Angle*	*Depth*	*Const*	*EU kW/h*	*DF%*	*DLS%*	*QV%*	*FC $*	*UC $*	*LCC $*	*CDE m.t.*	*Value*
1	4	0	20	1	0	GFRC	10316	2.06	0.95	1.75	131981	1314	194509	2.66	65
138	12	240	10	1	5	GFRC	8882	1.4	0.83	0.12	128815	1132	182648	2.29	53
212	12	240	30	9	5	GFRC	16590	3.38	0.97	0.36	174737	2114	275290	4.28	30
320	20	240	30	9	5	GFRC	16079	3.38	0.97	0.36	169046	2048	266500	4.15	34
426	4	240	10	9	5	SIP	13316	2.08	0.83	0.12	109660	1696	190369	3.43	40
517	12	240	20	9	0	SIP	15637	2.74	0.95	0.24	104240	1992	199017	4.03	43
605	**20**	**180**	**30**	**5**	**5**	**SIP**	**11797**	**3.08**	**0.97**	**1.13**	**104183**	**1503**	**175685**	**3.04**	**68**
728	4	120	30	9	0	CLT	18201	3.37	0.97	2	91824	2319	202145	4.69	48
801	12	180	10	5	0	CLT	11799	1.78	0.83	0.65	76928	1503	148445	3.04	55
924	20	120	10	5	5	CLT	11379	1.78	0.83	1.5	72188	1450	141160	2.93	61

4.4.4 Exploration

Value functions are useful for organizing these complex data sets, but it is important to provide other ways to allow the users to interact with the data to inform their decisions. Central to the framework is the use of parallel coordinates plots and visualization to understand and make trade-offs. The plot provides an understanding of how the *variables* affect the objectives as well as the overall *Value Function*. Figure 13 shows the entire design space. While the design alternatives and their options for every variable are to the left, the standardized weighted indicators and the value function to the right.

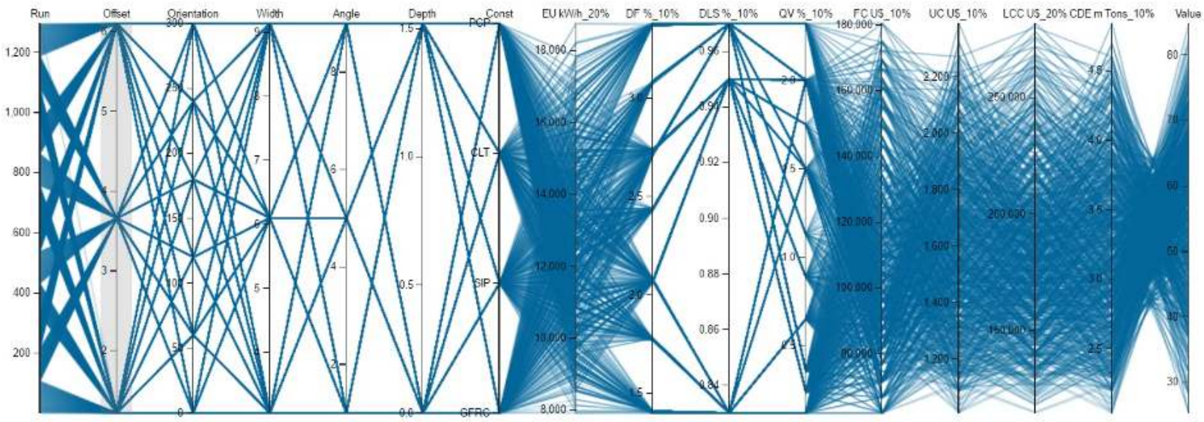

FIG. 13: Plot of the design space of 1296 alternatives.

The plot provides a process for discerning patterns, isolating and simplifying the display. By interactively selecting an interval of any coordinate, the *design space* is reduced to the set of alternatives that match the new threshold of values. Figure 14 shows the interactive filter of the alternatives with higher Energy Use (EU) or lower energy efficiency and the correlation between this indicator and small size windows and higher roof angle. This filtering feature helps to reduce a large amount of information into a smaller number of values and relationships.

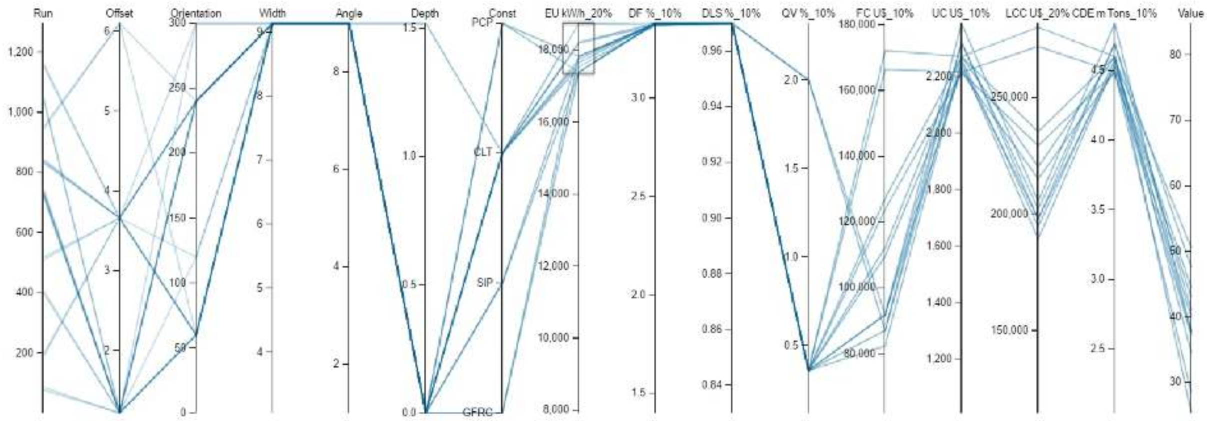

FIG. 14: Filtering alternatives within a threshold value looking for correlations.

Beside the filtering features, the custom plot also interactively allows the visualization of single alternatives (Fig. 15). This operation facilitates visualizing the trade-offs for preliminary assessments derived from different combinations of priorities of the indicators. The plot shows the *alternative* with maximum value (N°461) for a selective combination of weights: EU 50%, DF 20%, DLS 10% and QV 10%. EU has a significant influence in the value score of the chosen alternative. Even though the alternative has large windows, the low roof angle reduces the overall air volume of the building, and resulting energy losses. On the contrary, Figure 16 shows another combination of preferences assigning only 20% to EU and increasing the weight of DF from 20% to 50%. This inversion of *preferences* leads to a different *alternative* (N°533) that has similar floor plan, orientation and window size. While this *alternative* considerably increases the roof angle increasing the light coming through the clerestory (Fig. 17), it also increases the energy consumption that partially depends on the volume of the building. The interactive manipulation of *preferences* that defines *value* and the filters provide valuable feedback to the *problem formulation.*

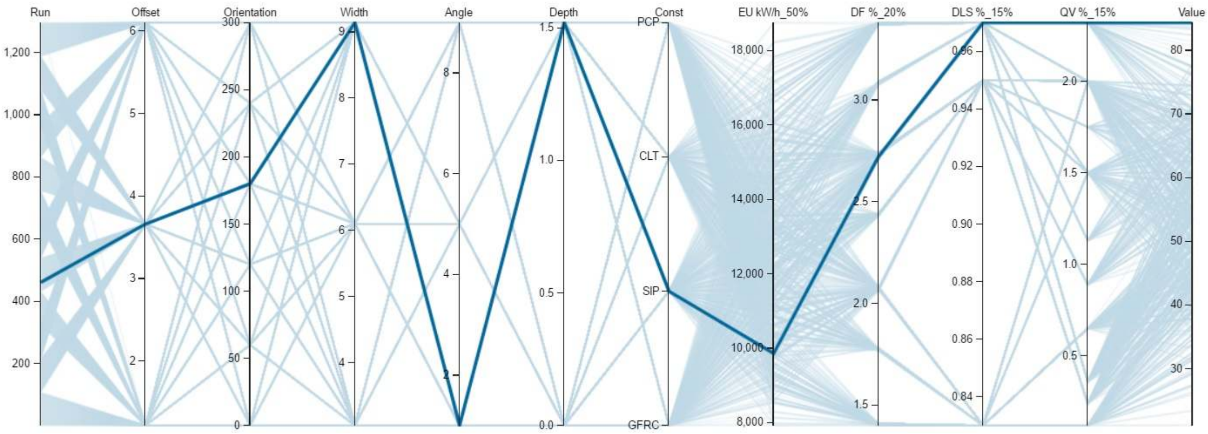

FIG. 15: Maximum value from a higher EU preference.

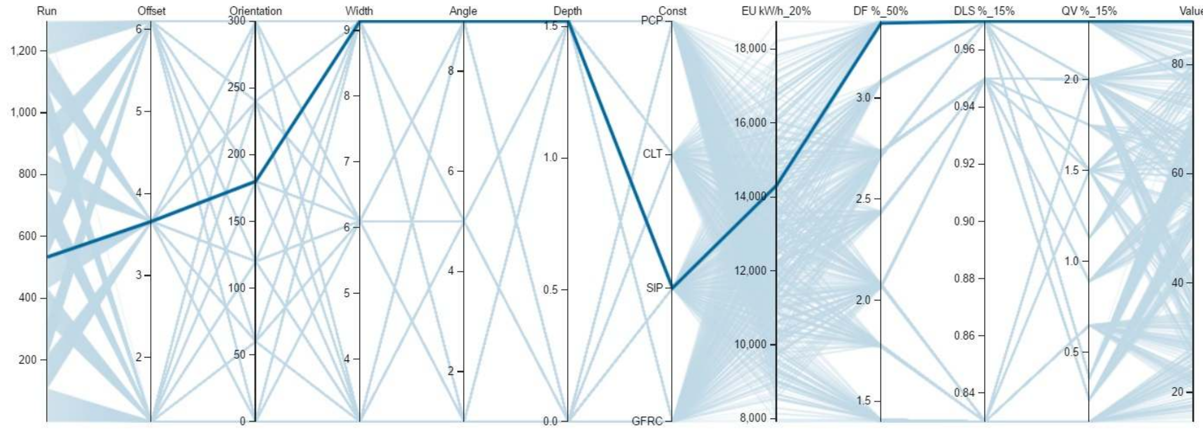

FIG. 16: Maximum value from a higher DF preference.

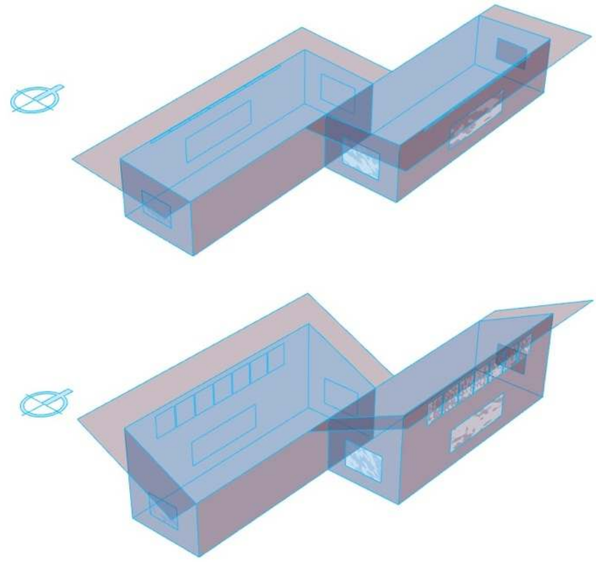

FIG. 17: Alternative 461 to the left, and 533 to the right.

5. FRAMEWORK VALIDATION

Validation is a process of building confidence in the usefulness of the set of methods, in this case, the extent to which the DSC framework enables a design team to efficiently and effectively construct and explore a design space. Validation of design methodologies (Pedersen, Emblemsvag, Bailey, Allen, & Mistree, 2000; Seepersad et al., 2006) can involve four stages. The first evaluates the internal structure according to the general problem. The second evaluates the appropriateness of the chosen case study for testing the usefulness of the proposed methodology or process. The third assesses the ability to produce useful results for the selected case. The last stage evaluates the capacity to produce general and powerful results beyond the chosen examples. In this particular study, the DSC framework implements a process deeply rooted in the decision-making literature; the relocatable classroom test case demonstrates the usefulness of the process to construct a design space and produce reliable results for similar problems using well-known industry standard analysis engines.

As to the fourth stage of validation, the design space construction framework has been iteratively developed and validated through an ethnographic and action research methodology (Hartmann et al., 2009). The framework and associated curriculum ("Design Space Construction Curriculum," 2016) has helped diverse teams of students and professionals to formulate, construct, and explore design spaces related to many types of building and urban scale design challenges ("Design Space Construction," 2016). We have implemented the DSC framework in 15 university courses and professional workshops, where over 200 students and professionals have implemented more than 40 design spaces.

To provide evidence for the power of the DSC framework, we worked with a professional project team designing the façade of an academic building in Canada to meet the stringent heating and cooling load requirements of the Passive House standard (Klingenberg, 2013) while also maximizing the available useful daylight within the space, as defined by LEED (USGBC, 2009). Figure 18 illustrates that the design decisions concerned how to distribute eight different predefined precast façade panels, position fins and overhangs, and define the U-values and Solar Heat Gain Coefficients for the glass, and the R-values for opaque walls. Figure 19 presents the actual DSC stages and loops, we executed.

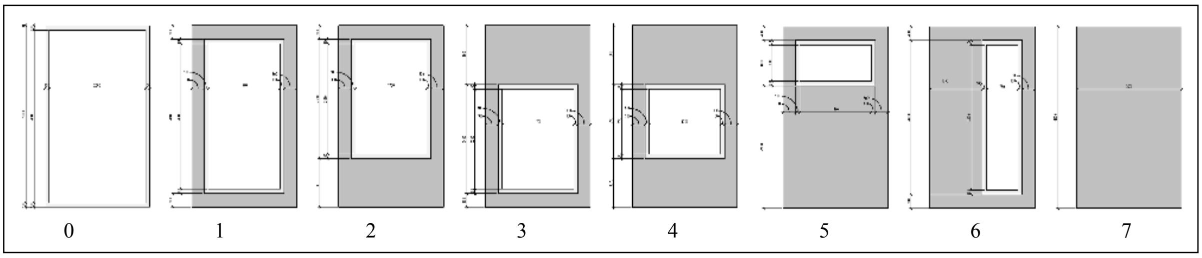

FIG 18: The case explored the selection of appropriate window panel options (0-7) and overhangs for the facades of an academic building.

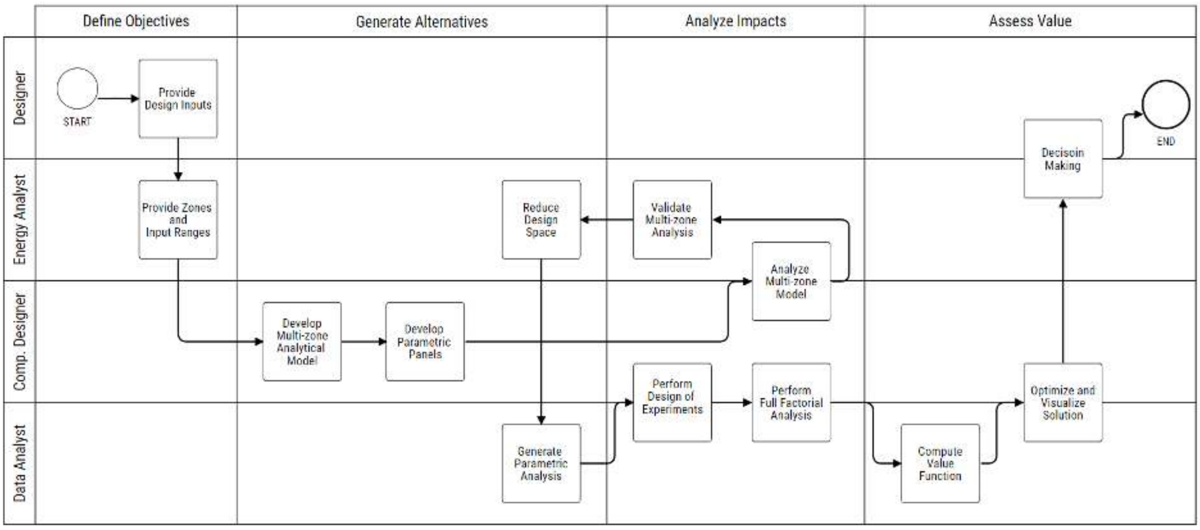

Fig 19: The DSC process applied to

We engaged the design team after they had developed a solution using traditional design methods. In addition, we asked two independent teams of senior designers to attempt to solve the same design challenge in a two-hour charrette (Clevenger, Haymaker, Ehrich, 2012) based on their professional experience. We gave the charrette teams performance feedback iteratively on individual design solutions, to simulate a point-based design exploration process, recording their best two designs from each team. We then worked with the project team to apply the DSC framework to the case study. Figure 20 & 21 show two results from these design explorations. Table 8 describes the heating, cooling, and daylighting values achieved by the charrette teams using their traditional methods and the ones from the DSC process, demonstrating how only the process developed using the

DSC framework allowed the design team to get closer to the Passive House requirements, while still achieving far better daylight penetration in to the space.

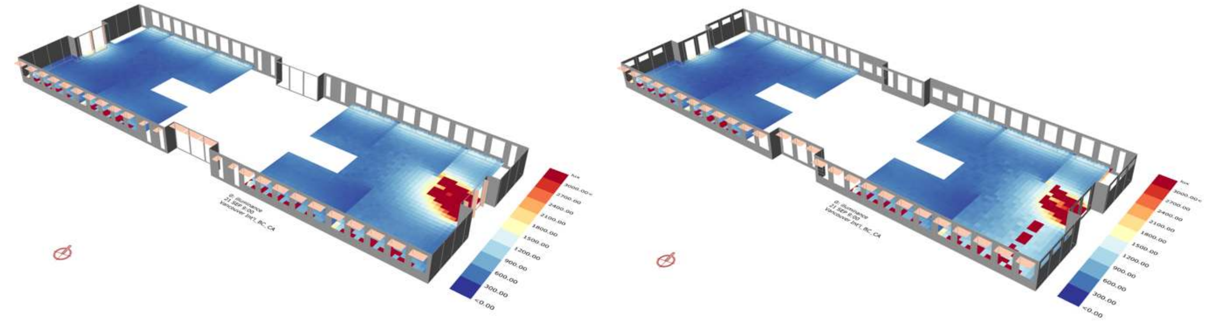

FIG 20: Visualization of the results of the charrette team 3 to the left, and the DSC process to the right improving the lighting score

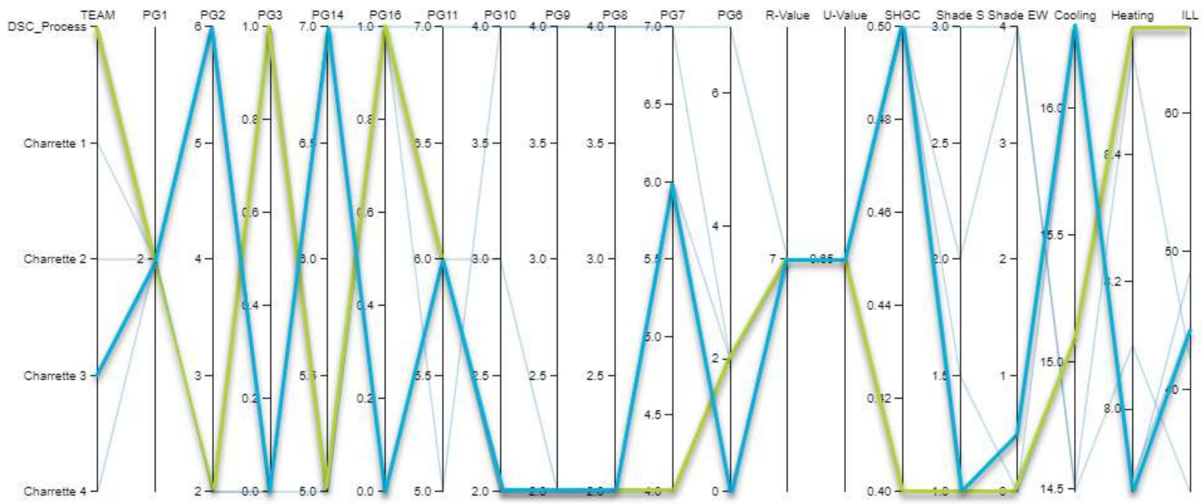

FIG 21: PCP demonstrating how the DSC process (green) allowed a design team to achieve better performance than traditional practice (light blue).

TABLE 8: Inputs and outputs from teams' choices.

TEAM	***PG1***	***PG2***	***PG3***	***PG14***	***PG16***	***PG11***	***PG10***	***PG9***	***PG8***	***PG7***	***PG6***	***R-Value***	***SHGC***	***Shading-S***	***Shading EW***	***Cooling***	***Heating***	***Illuminance***
Charrette 4	2	2	0	5	1	7	4	4	4	7	0	7	0.5	2	4	14.49	8.10	32.64
Charrette 3	**2**	**6**	**0**	**7**	**0**	**6**	**2**	**2**	**2**	**6**	**0**	**7**	**0.5**	**1**	**0.5**	**16.30**	**7.89**	**44.51**
Charrette 2	2	2	0	7	1	5	4	4	4	7	2	7	0.5	3	4	14.51	8.56	42.22
Charrette 1	2	6	0	7	0	6	3	2	2	6	2	7	0.5	1.5	0	16.32	7.87	48.51
DSC Process	**2**	**2**	**1**	**5**	**1**	**6**	**2**	**2**	**2**	**4**	**2**	**7**	**0.4**	**1**	**0**	**15.10**	**8.60**	**66.20**

To provide evidence about the generality of the DSC framework, we asked 16 professional and student computational designers in a workshop at a major international computational design conference to help us evaluate how well their firms and university curriculum constructed and explored design spaces. We then spent three days teaching the framework and helping them apply it to a similar façade panel case study. Given this in depth understanding of DSC, we then asked them to evaluate the extent to which they felt the framework would help their teams better and explore design spaces. Figure 22 illustrates that the students and professionals believed the framework would help them better construct and explore design spaces than the methods they are encountering in current practice and academia.

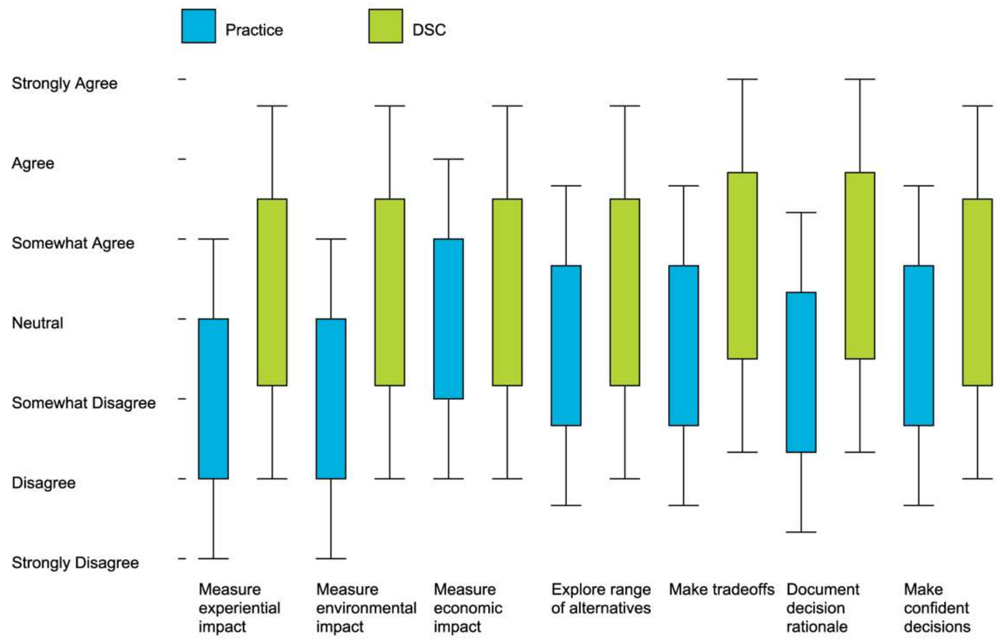

FIG 22: Data demonstrating the extent to which design professionals and students compared current practice in constructing and exploring design spaces compared to what they felt the DSC framework can enable.

6. CONCLUSIONS

All performance-based design teams construct and explore *design spaces*. However, design teams today typically use ad hoc processes and tools that do not clearly define performance metrics, alternative spaces, performance data, and decision rationale. Such unsystematic design processes lead to inefficient design exploration and loss of value. Beside the efficiency of the DSC approach presented in this paper, it demonstrates that generating and analyzing a larger set of design alternatives than current practice, and exploring different value functions according to stakeholders' preferences, enable design teams to improve the overall value by choosing better options for the input parameters that, otherwise, are very hard to find.

Nevertheless, in order to construct, explore, and communicate *design spaces*, design teams need to learn how to work together and adopt new tools and methods. Specifically, design teams need to execute the collaborative, iterative processes of *Problem Formulation, Alternative Generation, Impact Analysis,* and *Value Assessment*. The DSC approach, described through a test case, contributes with a framework and integrated computational workflow for each of above processes.

The framework provides the concepts and methods to enable a clearer and more systematic modeling of the decision-making process than current practice. However, still more systematic and iterative problem formulation are possible as extensions on this framework that can improve *stakeholder* engagement, *preference* elicitation, and design space reduction to assures the most efficient definition and exploration.

The workflow implementation that relies on the integration of parametric modeling and analysis tools in preliminary conceptual design stages provides consistent geometric representation and performance indicators early on for a large population of alternatives. However, even some of the processes described above are ad-hoc, and there remain several opportunities regarding interactivity, automation, scalability and extensibility of this modular structure to address analyses beyond the scope of the test case.

The real-time plot component integrates *stakeholders* in the decision-making process by helping them iteratively define preferences, identify key variables, and determine the overall notion of value. The methods can provide an important contribution in helping integrate requirements into the design process (Parsanezhad, Tarandi, & Lund, 2016) and to teach students and design teams to more systematically leverage emerging technologies into practice to address these requirements (Abdirad & Dossick, 2016)

Future work can improve the efficiency of generating designs, and deriving analytical input models for different analysis. The space of the designs can be more efficiently generated and explored using statistical and optimization methods, and cloud computing offers a vast computational infrastructure to extend the scope of the analysis to integrate other aspects such as cost, payback, spatial or structural analysis, security or life cycle of the buildings more quickly. The extensibility of the process implies an exponential growth of the search spaces, and points to the future development of strategies to improve the accuracy of the definition of the *ranges* and *options* of the *variables* to more efficiently and effectively define and explore design spaces in search of designs with the highest value.

7. ACKNOWLEDGEMENTS

The authors thank the Perkins+Will Research Board and design teams, and Georgia Institute of Technology's College of Design for their support of the Design Space Construction project.

REFERENCES

Abdirad, H., & Dossick, C. S. (2016). BIM curriculum design in architecture, engineering, and construction education: a systematic review. *Journal of Information Technology in Construction (ITcon), 21*(17), 250-271.

Arrow, K. J. (1971). Essays in the theory of risk-bearing. *Markham, Chicago, IL.*

ASHRAE, S. (2013). 90.1–Energy Standard for Buildings Except Low-Rise Residential Buildings. In: ASHRAE.

Becker, R. (2008). *Fundamentals of performance-based building design.* Paper presented at the Building Simulation.

Bernal, M. (2016). From Parametric to Meta Modeling in Design. *Blucher Design Proceedings, 3*(1), 579-583.

Brown, T. 2008. Design Thinking. Harvard Business Review.

Clevenger, C. M., & Haymaker, J. (2011). Metrics to assess design guidance. *Design Studies, 32*(5), 431-456.

Collopy, P., & Collopy, P. (1997). *Surplus value in propulsion system design optimization.* Paper presented at the 33rd Joint Propulsion Conference and Exhibit.

Council, U. S. G. B. (2016). LEED O+M: Existing Buildings | v4 - LEED v4. Daylight and quality views. Retrieved from http://www.usgbc.org/credits/existing-buildings/v4/indoor-environmental-quality.

Cross, N. (2004). Expertise in design: an overview. *Design Studies, 25*(5), 427-441.

Cross, N., Dorst, K. and N., Roozenburg (eds.) (1992) Research in Design Thinking, Delft University Press

DAYSIM. (2016). Retrieved from http://daysim.ning.com/.

Design Space Construction. (2016). Retrieved from http://designspaceconstruction.org

Design Space Construction Curriculum. (2016). Retrieved from https://www.gitbook.com/book/bernalm/design-space-construction/details.

EnergyPlus. (2016). Retrieved from https://energyplus.net/.

Flager, F., Welle, B., Bansal, P., Soremekun, G., & Haymaker, J. (2009). Multidisciplinary process integration and design optimization of a classroom building. *Journal of information technology in construction, 14*, 595-612.

Flux. (2016). Retrieved from https://flux.io, last accessed August 2017.

Geyer, P., (2009). Component-oriented decomposition for multidisciplinary design optimization in building design. Advanced Engineering Informatics, 23 (1), 12-31.

Hartmann, T., Fischer, M., & Haymaker, J. (2009). Implementing information systems with project teams using ethnographic–action research. *Advanced Engineering Informatics, 23*(1), 57-67.

Haymaker, J. R., Chachere, J. M., & Senescu, R. R. (2011). Measuring and improving rationale clarity in a university office building design process. *Journal of Architectural Engineering, 17*(3), 97-111.

Hazelrigg, G. A. (1998). A framework for decision-based engineering design. *Journal of Mechanical Design, 120*(4), 653-658.

HoneyBee & Ladybug. (2016). Retrieved from http://www.grasshopper3d.com/group/ladybug.

Hueting, R. (1990). The Brundtland report: a matter of conflicting goals. *Ecological Economics, 2*(2), 109-117.

Inselberg, A. (1997). *Multidimensional detective.* Paper presented at the Information Visualization, 1997. Proceedings., IEEE Symposium on.

Keeney, R. L., & Raiffa, H. (1993). *Decisions with multiple objectives: preferences and value trade-offs*: Cambridge university press.

Lawson, B., & Dorst, K. (2009). Design expertise. *Recherche, 67*, 02.

Lin S*, Gerber D.(2014) "Evolutionary Energy Feedback for Design: Multidisciplinary Design Optimization and Performance Boundaries for Design Decision Support," Journal of Energy and Buildings, Vol: 84, pp: 426-441

Local, E. (2017). Los Angeles, CA Electricity Rates. Retrieved from http://www.electricitylocal.com/states/california/los-angeles/.

OpenStudio. (2016). Retrieved from https://www.openstudio.net.

Parrish, K., & Tommelein, I. (2009). *Making design decisions using Choosing By Advantages.* Paper presented at the Proc. 17th Annual Conference of the International Group for Lean Construction (IGLC 17).

Parsanezhad, P., Tarandi, V. i., & Lund, R. (2016). Formalized requirements management in the briefing and design phase, A pivotal review of literature. *Journal of Information Technology in Construction (ITcon), 21*(18), 272-291.

Pedersen, K., Emblemsvag, J., Bailey, R., Allen, J., & Mistree, F. (2000). *Validating design methods and research: the validation square.* Paper presented at the ASME Design Theory and Methodology Conference.

Post, Allen, Harrison, P., & Turckes, S. (2017, June, 2017). Sprout Space. Retrieved from http://www.sproutspace.com

Radiance. (2016). Retrieved from https://www.radiance-online.org/.

Reichwein, A., & Paredis, C. J. (2011). *Overview of Architecture Frameworks and Modeling Languages for Model-Based Systems Engineering.* Paper presented at the Proceedings of the ASME 2011 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference.

Rothschild, S. S., & Pechan, E. (2009). *Total, Non-baseload, eGRID Subregion, State? Guidance on the Use of eGRID Output Emission Rates.* Paper presented at the 18th Annual International Emission Inventory Conference. U.S. Environmental Protection Agency OAP, Comprehensive Inventories -Leveraging Technology and Resources.

Rowe, G. Peter (1987). Design Thinking. Cambridge: The MIT Press.

RSMeans. (2017). Construction Cost Estimate. Retrieved from https://www.rsmeans.com/

Sadeghipour Roudsari, M., & Park, M. (2013). *Ladybug: a parametric environment plugin for grasshopper to help designers create an environmentally-conscious design.* Paper presented at the International IBPSA Conference, Lyon, France.

Sanguinetti, P., Bernal, M., El-Khaldi, M., & Erwin, M. (2010). *Real-time design feedback: coupling performance-knowledge with design iteration for decision-making.* Paper presented at the Spring Simulation Multiconference, Orlando, Florida.

Seepersad, C. C., Pedersen, K., Emblemsvåg, J., Bailey, R., Allen, J. K., & Mistree, F. (2006). The validation square: how does one verify and validate a design method? *Decision Making in Engineering Design, KE Lewis, W. Chen, and LC Schmidt, eds., ASME Press, New York.*

Suhr, J. (1999). *The choosing by advantages decisionmaking system*: Greenwood Publishing Group.

Turrin, M., von Buelow, P., & Stouffs, R. (2011). Design explorations of performance driven geometry in architectural design using parametric modeling and genetic algorithms. *Advanced Engineering Informatics, 25*(4), 656-675.

Zdrahal Z., Motta E. (1995). An In-Depth Analysis of Propose & Revise Problem Solving Methods. In: Proceedings of the 9th Banff Knowledge Acquisition for KBS Workshop (B.R.Gaines and M.Musen eds.), pp. 38-1–38-20.