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05.
CONSTRUCTING DESIGN SPACES:
Case Studies in Parametric Building Performance Analysis at Perkins and Will

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ABSTRACT
Parametric analysis is an important method for design exploration in architectural practice. However, architects do not take full advantage of its capabilities because they lack systematic methods for rigorous implementation. Design Space Construction (DSC) is a parametric analysis framework aimed at making multidisciplinary design exploration more methodical. This article discusses three case studies that have undertaken DSC for performance-driven building design. The reviewed projects involve massing and envelope configuration and construction decisions for a high school academic building, a high-rise commercial-residential development, and a university students' residence, all located in British Columbia, Canada. The article describes the processes used in executing DSC, the types of questions it helped answer, and the conclusions that the design teams drew from the process. We compare these outcomes to more typical simulation approaches used in practice. The article concludes with a discussion of the perceived benefits of DSC and the challenges faced constructing and exploring the design spaces.

KEYWORDS: design exploration, parametric analysis, design space construction, building performance analysis

1.0 INTRODUCTION

Architectural design is an exploratory process, described by Jones as comprised of analysis, synthesis and evaluation[1]. This process iteratively explores design requirements, synthesizes these requirements into design solutions, evaluates the extent to which solutions fulfill the requirements and then adjusts the solutions for a new round of iteration. Akin described it as a heuristic exploration through a set of design states in search of a design solution state[2].

Parametric analysis is a design exploration method that simulates a large number of design alternatives based on the combinatorial variation of design parameters. Parametric analysis is now a relevant design methodology in architectural design due to several factors, including increasing performance requirements on projects, computational design and analysis methods, and high performance computing. Parametric analysis for building performance has been an active area of research. Machairas et al. reviewed methods and tools for building design optimization[3]. Nguyen et al. reviewed simulation-based parametric analysis methods focusing on simulation programs, optimization tools, efficiency of optimization methods and industry trends[4]. Evins presented a review of significant research applying parametric analysis to sustainable building design problems[5].

However, research has also indicated that architects struggle to implement parametric analysis in practice. Gane and Haymaker have described the difficulty of design exploration due to lack of formal processes for translating multi-stakeholder requirements into specific parameters used to generate alternative spaces, and processes for understanding the impact of these parameters on multi-stakeholder value[6]. According to Clevenger et al., current practice fails to generate high quality design alternatives due to lack of systematic methods for evaluating the efficacy of design exploration processes[7].

Design Space Construction (DSC) is a formal methodological framework for problem formulation and solving that addresses the challenges of implementing parametric design exploration in practice, as seen in Figure 1. Haymaker et al. have defined DSC as a framework that guides teams through a process of Objective Definition, Alternative Generation, Impact Analysis and Value Assessment[8]. Such a systematic approach not only answers many of the questions architects face when attempting parametric design exploration, it also ensures such processes are efficient, replicable, scalable, robust and provide reliable quality of outcomes.

DSC assembles the relevant team members to establish the objectives of the design exploration and the criteria used for decision-making. This involves identifying the key roles of the process, specifically stakeholders, decision makers, designers and gatekeepers. Objective Definition involves defining key terms, including objectives, goals, constraints and preferences. Alternative Generation involves changing the options of design variables in order to develop large design spaces for exploration. Impact Analysis evaluates the influence of the options of an alternative on the design objectives. Value Assessment synthesizes impacts and stakeholder preferences into an objective function that orders the alternatives in terms of their suitability as design solutions.

The goal of DSC is to help a team construct and explore a Design Space. Figure 2 illustrates much of the information contained in a design space, displayed in a Parallel Coordinates Plot (PCP). Built to support a particular decision, it contains a list of the alternatives (sometimes in the thousands), the important design variables that characterize those alternatives, the performance of

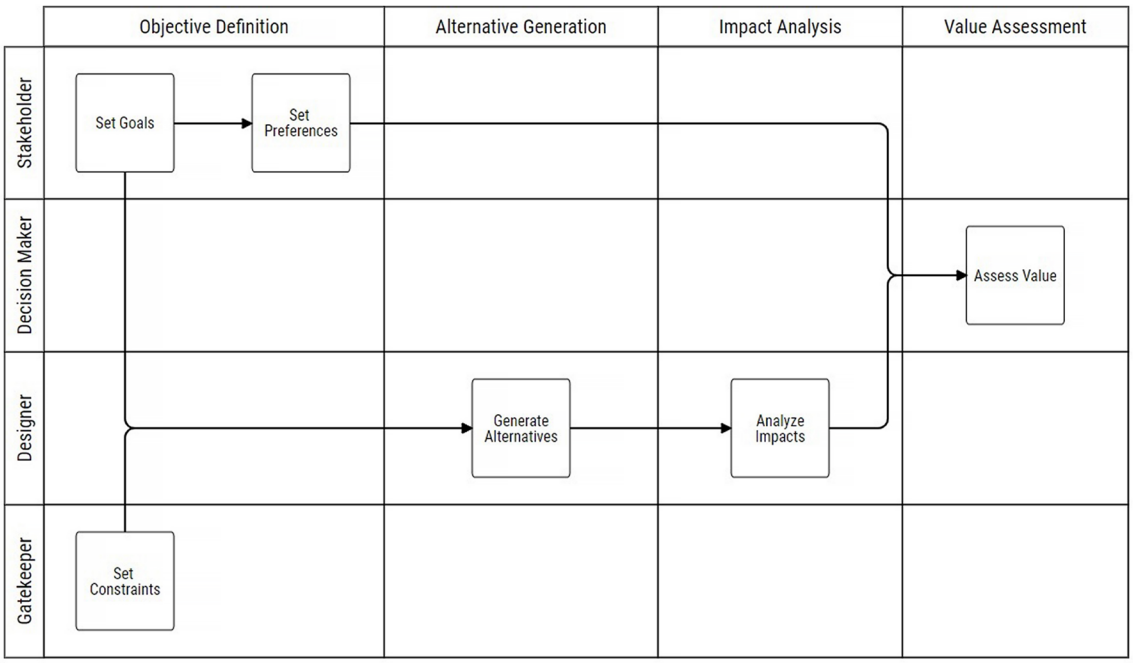


Figure 1: DSC formalizes a set of concepts and processes to help design teams construct and explore *Design Spaces*.

each alternative on any number of environmental, economic, and experiential goals. It is possible to combine and weigh these numbers to reflect a particular stakeholder's or group of stakeholders' values. In this way, it is possible to understand the impacts of particular inputs on outputs, as well as to order all alternatives from worst to first from a stakeholder's perspective.

We implemented DSC for the projects described in this article as a layered technological solution comprising analysis engines, plugins and wrappers, parametric modeling and data visualization interfaces, as shown in Figure 3. Analysis engines included Energy Plus[9] for energy analysis and Radiance[10] for daylight simulation, and bespoke analyses for views, first and lifecycle cost, and other objectives. Plugins and wrappers included HoneyBee[11] and LadyBug[12] both acting in the Grasshopper[13] for Rhinoceros[14] interface. We performed parametric modeling in Grasshopper. We performed Data Visualization within Design Explorer[15], a parallel coordinates plot (PCP) tool.

We have developed and validated DSC through ethnographic and action research-based methodologies. To date, we have engaged academia through the development and delivery of 15 University courses[16,17], at international conferences[18], and at internal workshops to over 200 students and professionals who have developed more than 100 design spaces. We have done this to understand the state of the art and develop robust tools and methods that can hope to meet the many needs of design professionals. We have also begun implementing DSC on projects, having completed more than a dozen projects at Perkins and Will at the time of publishing.

This article discusses three case studies, focusing on the implementation of DSC on projects undertaken in the Vancouver office of Perkins and Will. The projects are a high school development proposal, a mixed-use commercial-residential high-rise development, and a university students' residence. The goal is to highlight how, compared to traditional approaches, the DSC framework better enables design teams to define and answer questions with more confidence. The article describes the projects, defining the design questions that DSC sought to address, describing how we executed DSC, the design spaces constructed, and conclusions reached.

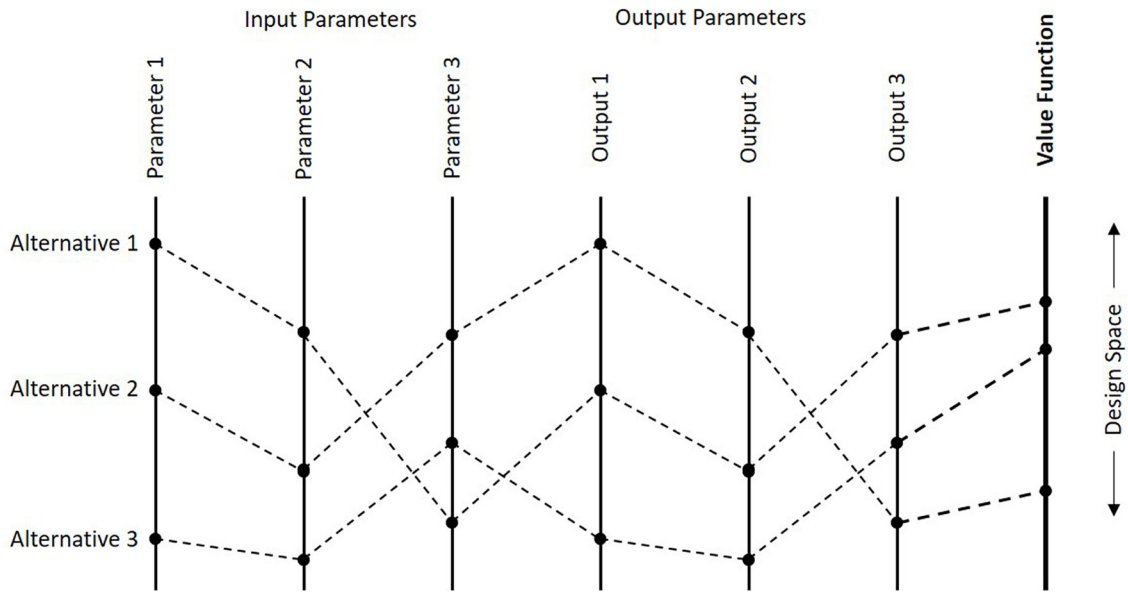


Figure 2: A PCP that describes much of the important information contained in a *Design Space*, and how it relates to different alternatives and variables.

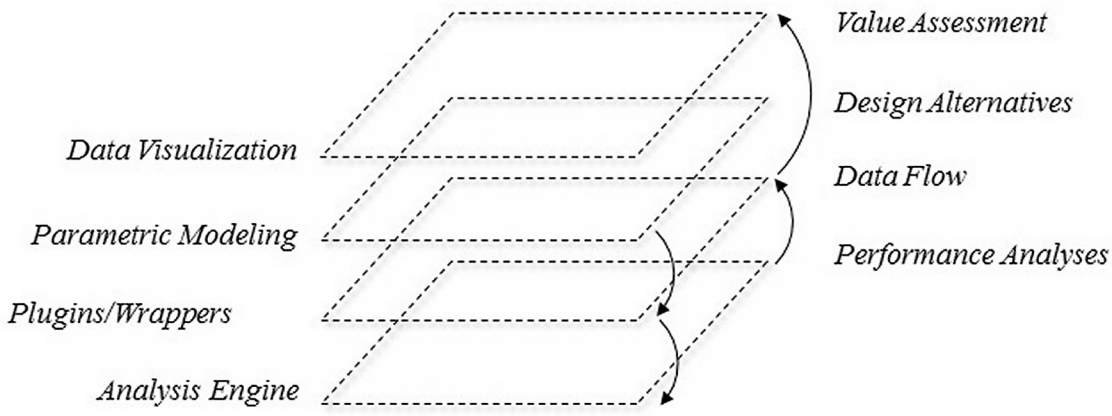


Figure 3: Layered implementation of DSC.

2.0 THE CASE FOR DSC

In order to understand the rationale for DSC it is useful to understand the types of questions that designers encounter when considering parametric design space exploration. These questions include: What output variables will best represent the design problem? What input variables correlate best with these outputs? How do these input variables relate to each other – for example, which input variables take priority over others? Who decides this priority and on what basis? How should we evaluate multiple, possibly conflicting, output variables? Practical implementation of parametric analysis has shown that we cannot simply run input and output simulations without answering these underlying questions. DSC was created as a framework that helps designers respond to these questions in a systematic fashion.

The integration of processes and roles into a single decision-making framework allows DSC to address these implementation questions. Chachere and Haymaker described how clarity of decision-making rationale can be incorporated into decision-making frameworks like DSC[19]. Such rationale answers questions relating to what variables are used for analysis, who decides on these variables and on what basis they make these decisions. Clevenger and Haymaker showed how frameworks like DSC can be used to measure the effectiveness of parametric analyses and the quality of design recommendations they provide[20]. This is important because not every analysis is suitable for every problem. Frameworks like DSC can provide useful metrics to assess the relevance of parametric analysis for design problem solving.

Architectural design problems are inherently multi-disciplinary, and effective architectural decision-making processes must take into account methods for analyzing multiple, sometimes conflicting, criteria. Although researchers have investigated multi-objective analysis for building performance, the incorporation of systematic frameworks like DSC enables designers to get the best value from the multi-objective analysis. Diakaki et al. performed a multi-objective analysis to evaluate the best design alternative for maximizing energy savings and minimizing construction costs[21]. Murray et al. investigated energy performance retrofitting using four criteria: capital investment, minimum energy cost post-retrofit, minimum carbon emission post-retrofit and maximum payback period[22]. While both these studies deal with conflicting multiple objectives, from an architectural perspective they are not truly multi-disciplinary. They are primarily concerned with energy performance and for the architect this is just one axis in multiple dimensions across which she must make decisions.

Multi-objective exploration of energy and daylight performance is a good example of architectural multi-disciplinary parametric analysis. Nielsen et al. argued that energy reduction and improved occupant comfort obtained from dynamic facades can only be achieved through an integrated process[23]. For example, improving internal daylighting can reduce artificial lighting energy consumption but at the same time increase heat gain. They used an integrated simulation process to perform multi-objective analysis by feeding the outputs of the daylighting analysis into the thermal simulation analysis. Ahmad et al. used machine learning as a sur-

rogate model for predicting hourly energy analysis and daylight illuminance[24]. The use of surrogate models for multi-disciplinary analysis is desirable because daylight simulations are typically time expensive.

Although both the above studies are multi-disciplinary, they do not provide a systematic method for assessing the combined value of conflicting objectives. One approach is to develop a multi-objective value function and use optimization methods, such as *Pareto Front* analysis. Lartigue et al. recognized a gap in performing multi-objective analysis for both daylight and energy load optimization[25]. They proposed a methodology for simultaneously optimizing heating load, cooling load and illuminance using an objective function to establish Pareto-optimal solutions. Flager et al., borrowing from the aerospace and automotive industries, investigated the application of multi-disciplinary optimization for structural and energy performance[26]. They used *Pareto Front* optimization to analyze structural cost vs. energy cost for a reference classroom building.

While these efforts are noteworthy for appropriately incorporating value functions into the analysis, the processes they describe are incomplete. They lack decision-making rationale clarity. While the use of value functions makes the evaluation of conflicting objectives more systematic it does not account for different strategic roles in decision making. This risks developing solutions that are satisfactory from one point of view (such as the designer) but which lack relevance for some other role in the decision-making framework. By integrating roles and processes and by incorporating mechanisms for multi-disciplinary optimization, DSC seeks to address many of the challenges arising from implementing parametric design exploration in practice.

3.0 HIGH SCHOOL ACADEMIC BUILDING ENVELOPE STUDY

The school campus has 775 students in grades 8 through 12. The school sought to replace existing high school buildings using a phased masterplan approach. This resulted in a Phase 1 masterplan, consisting of three buildings: two academic buildings and a dining hall building accommodating a wide variety of indoor and outdoor spaces for informal learning and socializing. The project's design principles included: 1) maximizing connections to the outdoors, both physical and visual; 2) creating academic and athletic facilities with the flexibility and adaptability to change; 3) establishing a new heart of the campus; 4) simplifying and clarifying circulation; and 5) demonstrating leadership in sustainability.

The design team engaged the authors once they had agreed upon the buildings programming and design, and focus was now on the design of a facade system. The team was pursuing a prefabricated panel concept, which would work well with the cross-laminated timber (CLT) structural system and modules already selected as the primary building structure. The idea was a simple, elegantly designed facade, designed from the inside out with a choice of stone inlays, pressed metal

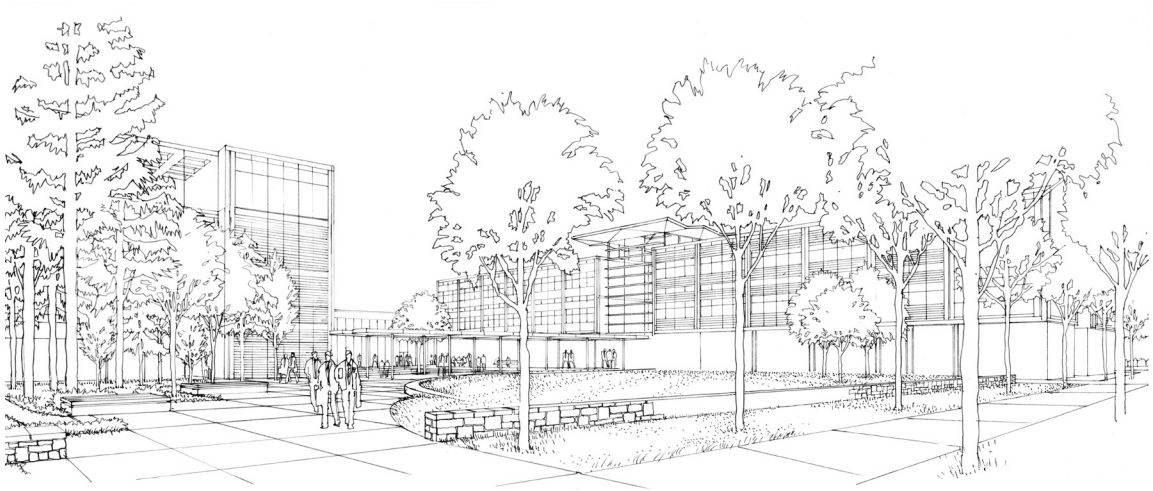


Figure 4: A design sketch of the high school academic project.

panels or fins and louvres as the exterior material expressions. Designers expected that panel material and the opaque/transparency ratio would be big drivers of overall building performance. They wanted to understand how these factors, in the context of the building's site and program, influenced energy and daylight performance, and their ability to meet Passive House[27] and LEED[28] rating criteria.

3.1. DSC Process

The design team decided to conduct the DSC exercise at first on just one of the three buildings—the Arts and Sciences building. It had three levels, and about 200 possible panel locations on its facade. Given that they were considering about 10 panel types, the raw number of possible panel combinations was 10^{200}. This number is not computable. Therefore, the first consideration in performing DSC was to define a design space reduction strategy. Such a strategy would reduce the amount of simulations required without compromising how representative the simulated sample was of the overall design space.

Figure 5 describes, at a high level, the process that the team undertook to construct the design space. They identified four roles for the DSC process: *Designer, Energy Modeler, Computational Designer* and *Data Analyst*. The *Designer* represented the design team in the process and helped to define goals, objectives, preferences and parameter input ranges. The *Energy Modeler* helped the designer define realistic input parameters and parameter ranges, defined the zoning for energy analysis and provided zoning input data for the simulation. The *Designer* and *Energy Modeler* were also involved in interpreting the results for design decision making. The *Computational Designer* developed the

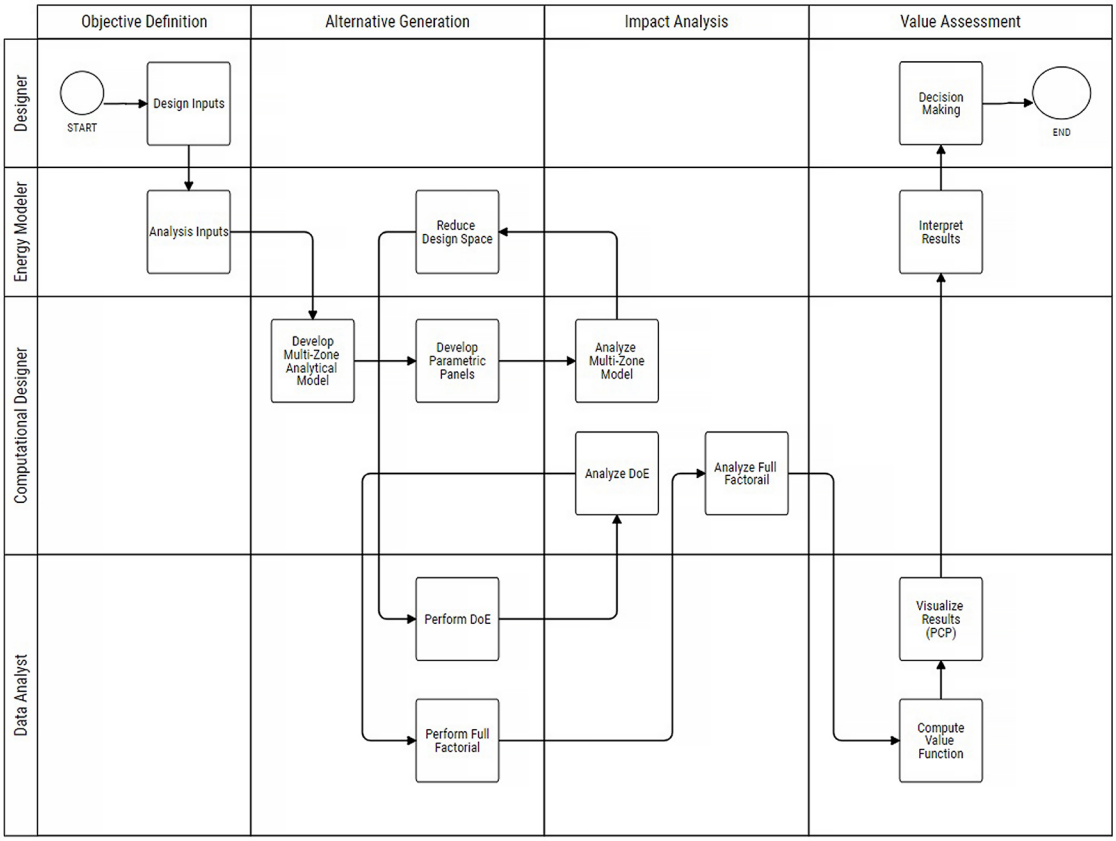


Figure 5: High school DSC process and team member roles.

parametric geometry for analysis, processed all analysis inputs in the DSC script and executed the actual simulations, publishing the results to a data visualization interface. The *Data Analyst* used a design of experiments (DoE) to define a reduced sample space for simulation. DoE is a statistical method that is effective in design space reduction of large design spaces. The *Data Analyst* also performed statistical tests and sensitivity analyses to support interpretation of the results.

3.2 Objective Definition

The project sought to achieve Passive House certification. A key requirement of Passive House certification is that both the heating demand and cooling demand are below 15 kwh/m^2/year[29]. However, recognizing that this is a school and that daylighting is important, the design team also sought a solution that would optimize daylighting in the key activity spaces. They sought the LEED v4 Daylighting credit that requires illuminance levels between 300 lux and 3,000 lux for 9 am and 3 pm, both on a clear sky day at the equinox[30]. The DSC became an exercise in the multi-objective optimization of facade panels in order to try to meet the Passive House and LEED v4 energy and daylighting criteria.

3.3 Alternative Generation

The design team and DSC team worked together to choose different panel configurations to consider and determine what combination of panels provided the best design expression, while also providing optimized energy and daylighting performance, as seen in Figure 6.

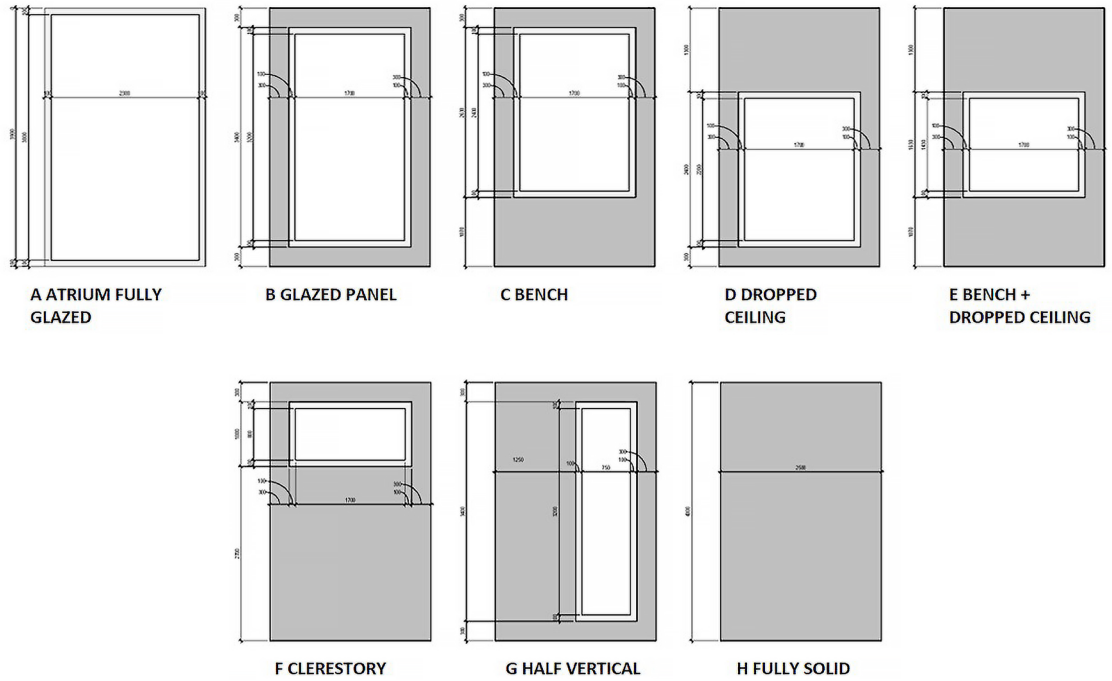


Figure 6: High school panel alternatives.

3.4 Impact Analysis

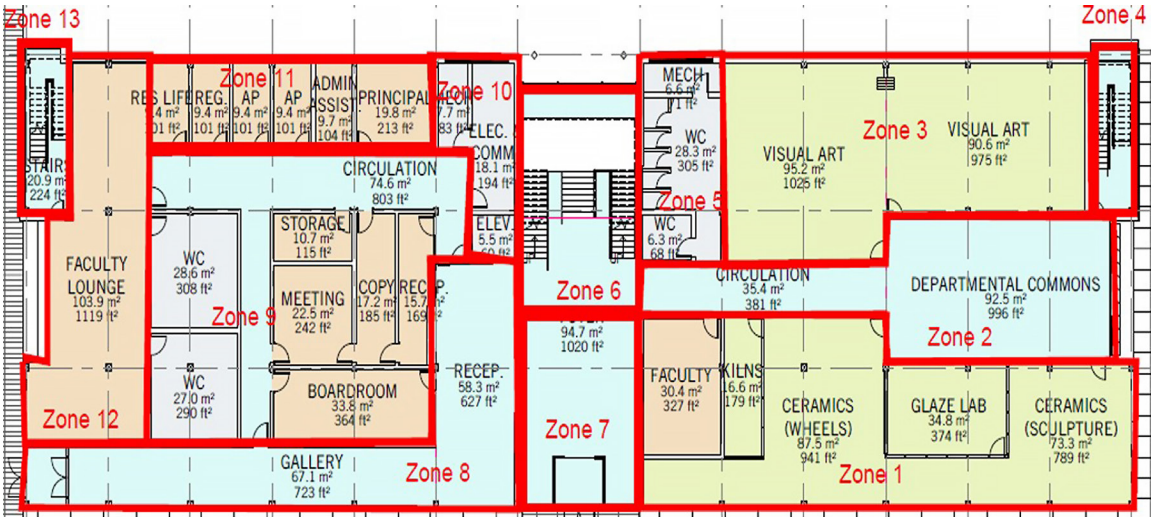
The DSC team reduced the *Design Space* through three distinctive steps: designer intuition, zone-by-zone energy analysis and "design of experiments." They asked the *Designer* to use their intuition and experience to identify which panel types were most suited to the different program areas of the design, as shown in Figure 7. The *Designer* defined shading depth and orientation as part of the panel design parameters, as well as solar heat gain coefficient (SHGC) ranges related to glazing within the panels. Designer intuition had the effect of reducing the *Design Space* to about 288,000,000 combinations, which is still out of practical range.

The DSC team undertook zone-by-zone energy analysis to reduce the design space further. They argued that since the Passive House energy requirements were more prioritized, it made sense to filter down the design space by first identifying suitable ranges of design inputs for energy performance. Zone-by-zone analysis would provide a quick way to identify the most appropriate parameter ranges and panel selections for each individual zone of the building. They based the parameter ranges for the full building analysis on the worst-case outputs of the zone-by-zone analysis. They defined thirteen zones per level and performed about 800 energy simulation runs. Based on this step, a final *Design Space* of 13,824 combinations of inputs and panels was identified, as seen in Figure 8.

While 13,824 alternatives is not a prohibitive number, it is still quite high for a multi-objective design exploration involving both energy and daylighting. Run time for each simulation was estimated at about two minutes on standard equipment (for example, Lenovo ThinkPad X1 Yoga; Intel Core i7-7600U CPU @ 2.8 GHz, 2 Cores; 16GB RAM). This would result in a run time of about 20 days. Further design space reduction was required, and it was achieved using a "design of experiments" approach (Figure 9). This reduced the *Design Space* to 288 simulations, which executed in about two hours using a parallel processing approach on a high performance computer (ProLiant DL380p Gen8; Intel® CPU e5-2640 0 @ 2.50 Ghz, 2492 MhZ, 6 Core(s), 12 Logical Processor(s), 2 Cores; 128GB RAM).

AREAS	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Description	Science La	Social/ learn	Atrium (S)	Circulation	Art (S)	Atrium (N)	Mechanica	Learning	Learnir	Faculty	Stairs	Art (N)	Admin	End	GF End	Atrium (E/W)
Target Glazing Ra	0.24-0.54	0.24-0.87	0.7-0.9	0.75-1	0.75-1	0.4-0.87	0-0.25	0.24-0.54	0.24-0.	0.24-0.54	0-0.41	0.14-0.	0.24-0.54	0-0.25	0.54-0.87	0.54-0.87
Panel Types	B, C,E,G	A,B,C,D,G	A, B	A,B,C,D,G	A,B,C,D,G	A,B,C,D,	E,F,H	C,D,E,F,G	C,D,E,F	C,D,E,F,G	F,G,H	F,G,	C,E,F,G	F,H	A,B	A, B
Shading	Y (1,2,3)	Y (1,2,3)	Y (1,2,3)	Y (1,2,3)	Y (1,2,3)	N	N	N	N	N	N	N	N	N	Y (1,4,5)	Y (1,4,5)
SHGC	1,2,3	1,2,3	1,2,3	1,2,3	1,2,3	1,2,3	1,2,3	1,2,3	1,2,3	1,2,3	1,2,3	1,2,3	1,2,3	1,2,3	1,2,3	1,2,3

Figure 7: High school facade areas and *Design Space* reduction by designer intuition.



Inputs	PG1	PG2	PG3	PG6	PG7	PG8	PG9	PG10	PG11	PG14	PG16	R-Value	U-Value	SHGC	Shading_N	Shading_S	Shading_EW
Options	CE	CD	B	CD	E	CE	CE	CE	G	GF	B	6,7	0.65,0.7	0.3,0.4,0.5	0	0,0.5,1	0,0.5,1
Number	2	2	1	2	1	2	2	2	1	2	1	2	2	3	1	3	3
Full Factorial	C	CD	B	CD	E	CE	CE	CE	G	F	B	7	0.65	0.3,0.4,0.5	0	1	0,0.5,1
Number	1	2	1	2	1	2	2	2	1	1	1	1	1	3	1	1	3
																	13824 RUNS

Figure 8: High school zone-by-zone analysis and final *Design Space* of 13,824 alternatives.

Run	PG1	PG2	PG6	PG8	PG9	PG10	PG14	R-Value	U-Value	SHGC	Shading-S	Shading-EW
60	E	C	C	E	E	C	G	7	0.65	0.4	0	1
61	E	C	D	E	E	C	G	6	0.7	0.3	1	0
62	C	D	D	C	E	C	G	6	0.65	0.5	0	0.5
63	C	C	C	C	E	C	F	6	0.65	0.5	0	1
64	C	D	C	E	C	C	G	6	0.7	0.4	0.5	0.5

Figure 9: High school after "design of experiments."

In addition to *Design Space* reduction, the computational designer developed a spreadsheet driven parametric panelizing process in Grasshopper, as seen in Figure 10. This was responsible for the different combinations of panel selections available to the simulation process. Once the simulations were complete, they visualized and interpreted results using a PCP interface, shown in Figure 11.

3.5 Value Assessment

A number of design alternatives met both the Passive House heating demand and cooling demand requirements. Simultaneously achieving the LEED v4 daylighting metric was more challenging. The DSC process identified a design alternative that could provide 66 percent of usable floor area with between 300 lux – 3000 lux. This was demonstrably better than what unaided designers could achieve. To make this comparison, we conducted a design charrette in Vancouver in September 2017. Participating design teams analyzed the high school building and proposed solutions that would satisfy the Passive House energy requirements and the LEED v4 daylighting requirement. As shown in Figure 12, while able to achieve the Passive House requirements, designers identified solutions with 48 percent daylighting in the required range—significantly lower than DSC.

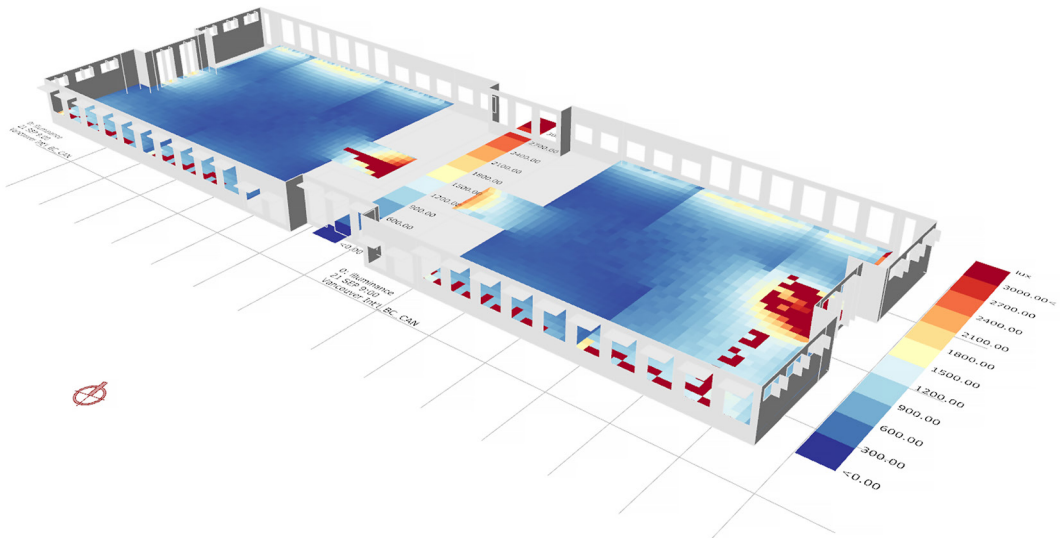


Figure 10: High school panelizing and analytical model.

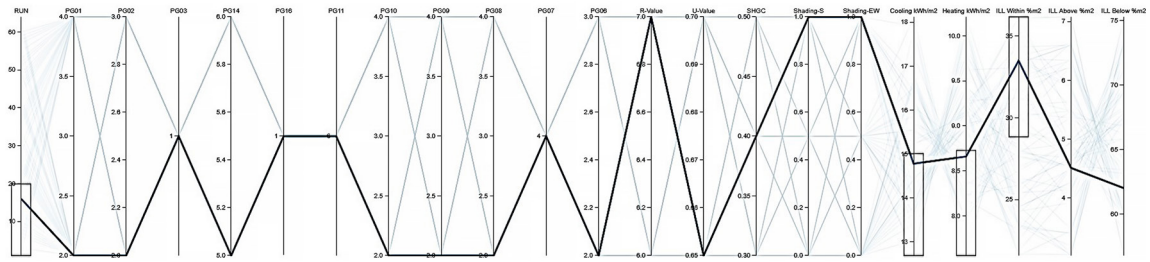


Figure 11: High school building partial PCP.

	Cooling Load (kWh/sqm/y	Heating Load (kWh/sqm/y	Illuminance (% 300>3000 lux)
Project Team	14	8.25	35
Charrette Team 1	14.5	8.6	43
Charrette Team 2	16.5	7.9	48
DSC Team	15	8.7	66

Figure 12: High school DSC design charrette. Designers versus the DSC process.

4.0 RESIDENTIAL TOWER MASSING AND FACADE STUDY

This was a commercial residential development situated in the neighborhood of East Vancouver, consisting of a highly insulated tower clad in clear glass with shadow box assemblies. The tower base featured a series of retail spaces and a street-oriented lobby. The designers proposed a community library on the second and third floors, while at the top of the tower they proposed amenity spaces housed in a double height space featuring a communal lounge, a mezzanine library with views to the city, mountains and water, and an outdoor pool area.

The design was inspired both by the character of the neighborhood as well as by the heritage of Northwest modernist tradition of lightweight structural systems, nautical concepts of outriggers and tension elements, and contemporary concepts of prefabrication and plug-in-play assemblies. The design team proposed lightweight balconies of undecided depth to create outdoor living rooms. They intended the balconies to provide full solar shading during peak demand, load hours. The balconies also featured planters for privacy and additional screening elements designed as plug-in-play elements of the facade. The team proposed constructing the balconies from lightweight steel outriggers suspended by a network of steel cables, minimizing the thermal bridging and creating a diaphanous scrim for the tower. To create design interest, they proposed a dramatic horizontal shift in geometry at mid-tower height, as seen in Figure 13.

4.1 DSC Process

Once the design team had settled the overall program and massing of the building, they engaged the DSC team. The designers were looking for guidance on how to modify the form and envelope of the massing to optimize energy and daylight performance. They were also looking for guidance on the impact of the building form shift on building performance, as well as the appropriate dimensions and configurations of the balconies and facade elements.

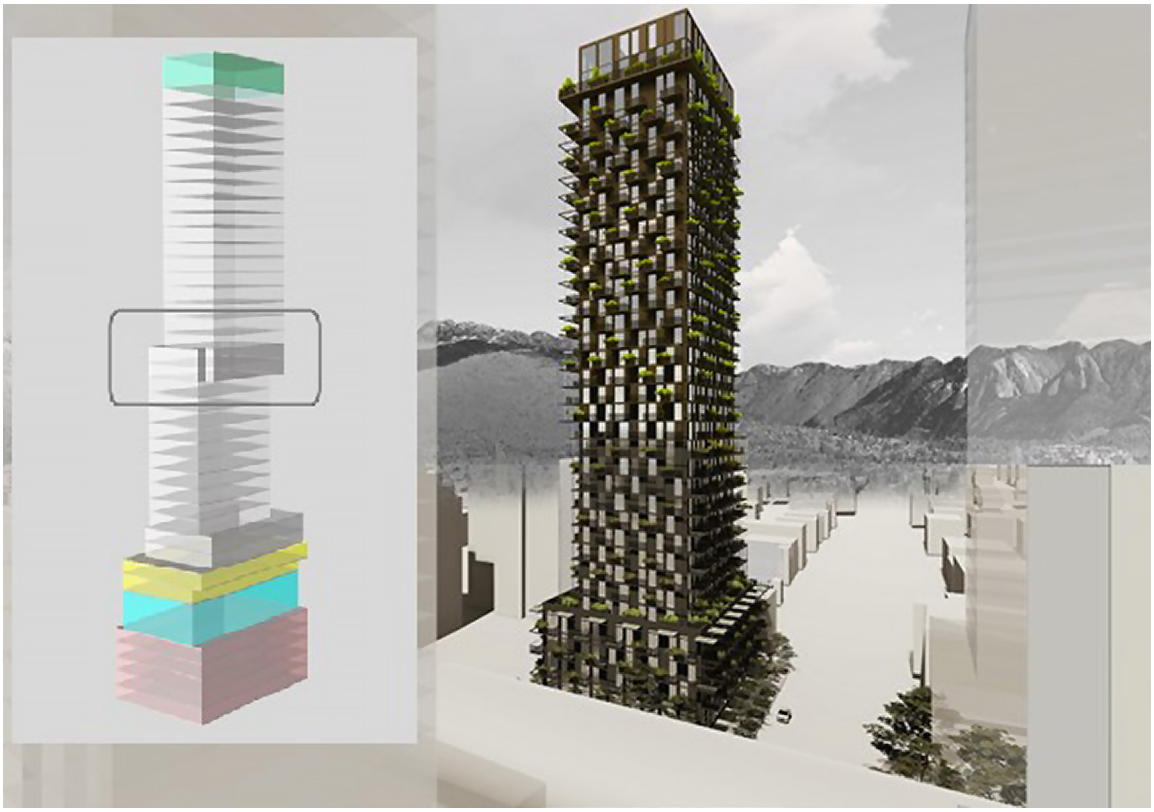


Figure 13: Residential tower design impression. Inset: proposed tower shift.

4.2 Objective Definition

According to the City of Vancouver Green Building for Rezoning standards[31], which all rezoning applications need to meet, projects have a choice between pursuing Near Zero Emissions Building (NZEB) or Low Emissions Green Building (LEGB). The NZEB pathway requires teams to design projects to Passive House or an alternative similar standard. The key metrics of this pathway are space heating demand at 15 kWh/m^2/year, 0.6 ACH @ 50 Pascals pressurization, and maximum 60 kWh/m^2/year renewable primary energy demand.

The LEGB pathway requires LEED Gold Certification[32] or an alternate holistic green building rating system. For residential high-rise towers, Total Energy Use Intensity cannot exceed 120 kWh/m^2/year, Total Energy Demand Intensity 32 kWh/m^2/year and a Green House Gas Inventory of 6. However, it also has a list of additional requirements, including requirements for whole-building airtightness testing, requirements for enhanced commissioning and about a dozen more provisions. Therefore, the design team wished to understand which of these pathways was most feasible for their design objectives. Were the stringent NZEB Passive House energy requirements attainable or was it better to focus on the less stringent, but more numerous requirements of the LEGB pathway? In addition, the design team sought to optimize energy, daylight and comparative cost considerations.

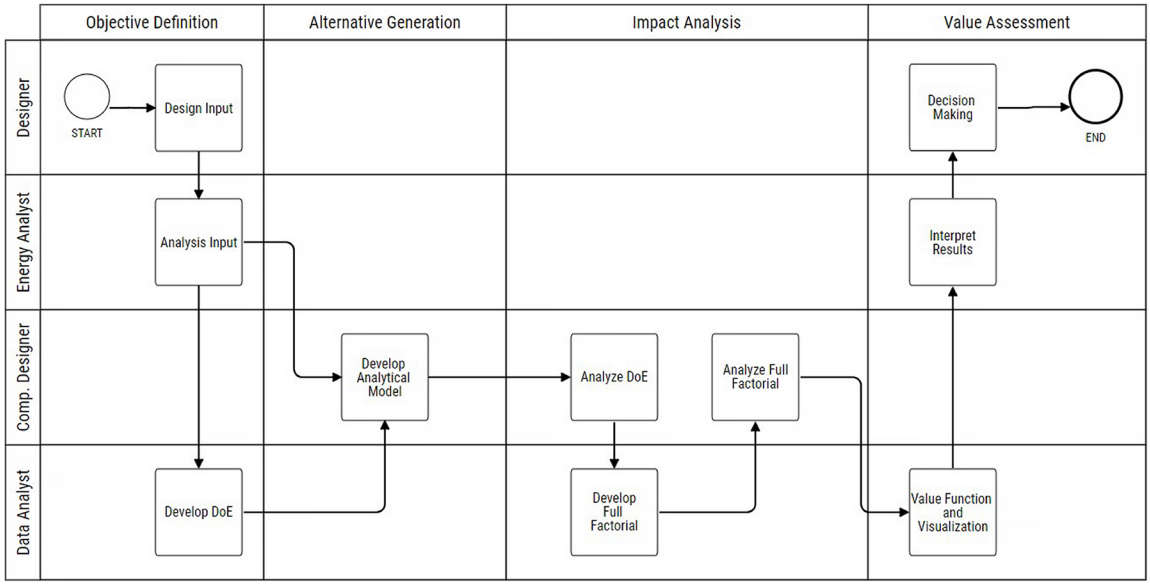


Figure 14: DSC process for the residential tower massing and facade study.

4.3 Alternative Generation

Which design alternative could meet the rezoning energy requirements, while providing the best daylighting and views at the lowest first cost? In particular, both the developer and the designer wished to use 50 percent window to wall ratio (WWR) on all facades, because daylight and views are an important selling feature in the high-rise condominium market in Vancouver. However, by running preliminary PHPP calculations, the Passive House consultant recommended 42 percent WWR in order to give a better chance of achieving Passive House requirements. The team hoped that DSC would help inform this decision.

Designers understood that balcony design and installation would have an impact on performance considerations. They intended the cantilever balcony to act as a sun-shading device but, at the same time, they considered the installation points as thermal bridges adversely influencing thermal performance of building envelope. The design team expected DSC to help identify the optimal balcony depth on each facade that provided energy benefits, without compromising daylighting performance or introducing significant thermal bridging.

4.4 Impact Analysis

The team undertook DSC on the Joyce Street project at two levels of the tower, below and above the proposed mid-height shift. The team modeled a representative level for the levels 14 to 28 above the shift, and another representative level between levels 3 to 13 below the shift. Although the program configuration was different above and below the shift, simulation results found no significant difference in performance. Therefore, generalization from the two selected levels was an adequate approximation.

The *Designer* and *Energy Modeler* identified the ranges of relevant input variables as well as the metrics for the design questions discussed above. The *Energy Modeler* then created the zoning for the analytical model and provided the zone assumptions for the energy simulation. The *Data Analyst* and the *Computational Designer* downloaded the ranges of the input variables and the zone input data respectively.

Given the proposed variables and input ranges, the full *Design Space* included about 2 million alternatives. A *Design Space* reduction was required. The team used a "design of experiments" method to reduce the design space to 1296 simulations. First, they simulated 64 runs of levels 3 to 13 and levels 14 to 28 to design the experiment. Then, they developed a full factorial design of 1296 simulations based on the results of the simulations. They passed on the results to the computational designer. The *Computational Designer* modeled the zones processed the zone input data, executed the simulations and posted the results to Design Explorer.

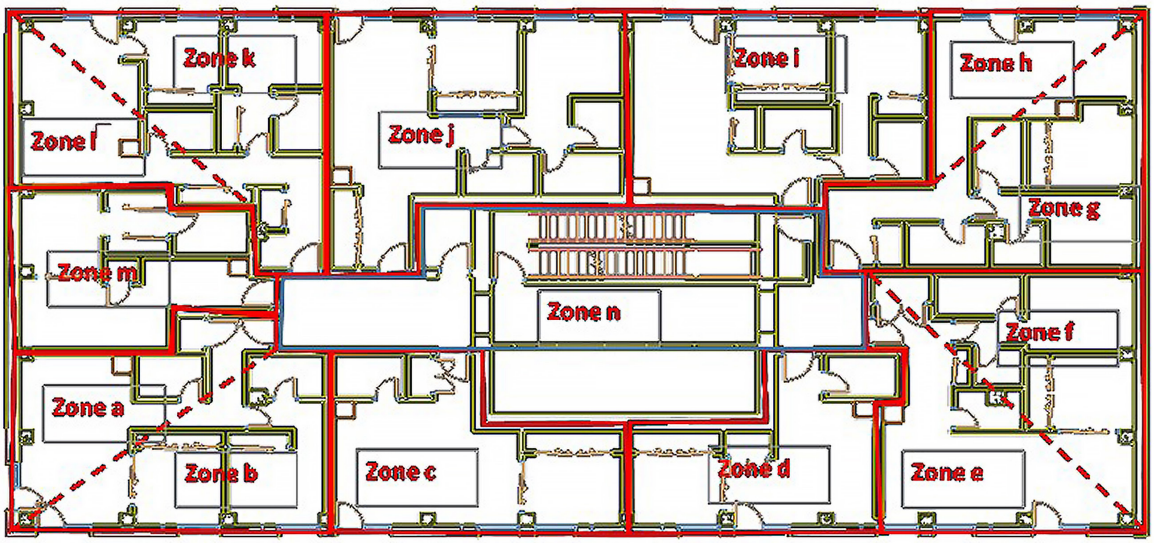


Figure 15: Residential tower typical zoning on levels 3 - 13.

Window to Wall ratio (%)	Effective U value (W/m2K)	Win U/SHGC	Balcony/Shades depth (ft)
30	0.40	0.85/0.3	0
	0.30	0.85/0.5	
	0.25	0.85/0.7	5
	0.33	1.4/0.3	
	0.23	1.4/0.5	10
	0.19	1.4/0.7	
40	0.41	0.85/0.3	0
	0.32	0.85/0.5	
	0.27	0.85/0.7	5
	0.34	1.4/0.3	
	0.24	1.4/0.5	10
	0.19	1.4/0.7	
50	0.44	0.85/0.3	0
	0.35	0.85/0.5	
	0.30	0.85/0.7	5
	0.35	1.4/0.3	
	0.25	1.4/0.5	10
	0.20	1.4/0.7	
60	0.48	0.85/0.3	0
	0.39	0.85/0.5	
	0.34	0.85/0.7	5
	0.36	1.4/0.3	
	0.27	1.4/0.5	10
	0.22	1.4/0.7	
70	0.55	0.85/0.3	0
	0.45	0.85/0.5	
	0.40	0.85/0.7	5
	0.39	1.4/0.3	
	0.29	1.4/0.5	10
	0.25	1.4/0.7	

Figure 16: Residential tower ranges of input variables.

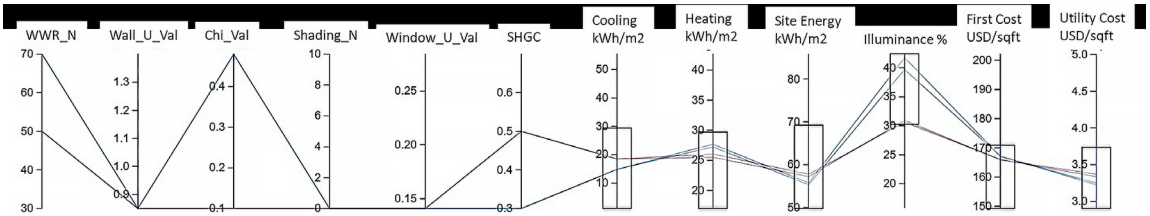


Figure 17: Residential tower partial PCP.

4.5 Value Assessment

The findings from the residential tower indicated that both Passive House heating demand and cooling demand could be achieved only with an efficient heat recovery system. Both 40 percent WWR and 50 percent WWR met the cooling requirement, and both failed to meet the heating requirement without heat recovery. Larger (50 percent) WWR was obviously superior in terms of daylighting, and the DSC recommendation was that 50 percent WWR should be further investigated through more detailed modeling. The design team proposed 5 feet deep balconies on north and east facades, and 10 feet balconies on the south and west facades. There was no significant difference in building performance by reducing the depth of balconies along the south and west facades to 5 feet.

5.0 UNIVERSITY STUDENTS' RESIDENCE MASSING AND ENVELOPE STUDY

The University Students' Residence project is a 330,000 sq. ft. student housing, dining and conferencing facility located in British Columbia. The project is located at the intersection of two important promenades, and presented an opportunity to strengthen the campus circulation network. The design sought, among other criteria, to incorporate passive design principles, and reduce energy consumption, Green House Gas (GHG) emissions and address future climate resilience, creating a showcase project for the university (Figure 18).

Figure 18: University Students' Residence, design impression.

5.1 DSC Process

The design team engaged the authors in the early massing development phases. The key question was which of three massing options was most suitable for design development in terms of optimal energy and daylighting performance. The investigation required three different DSC analytical models to be developed and cross-compared, shown in Figure 19.

Similar to the previous projects, the DSC process involved the four roles of *Designer, Energy Analyst, Computational Designer* and *Data Analyst* (Figure 20). The team developed three DSC analytical models based on a typical level from each of the design options (Figure 21). They based the full design space on the inputs shown in Figure 22. "Design of experiments" method was used to define three design spaces of 64 simulations for the three massing options. The team compared the massing options in terms of energy, daylighting and total site energy.

Figure 19: Massing options for DSC analysis.

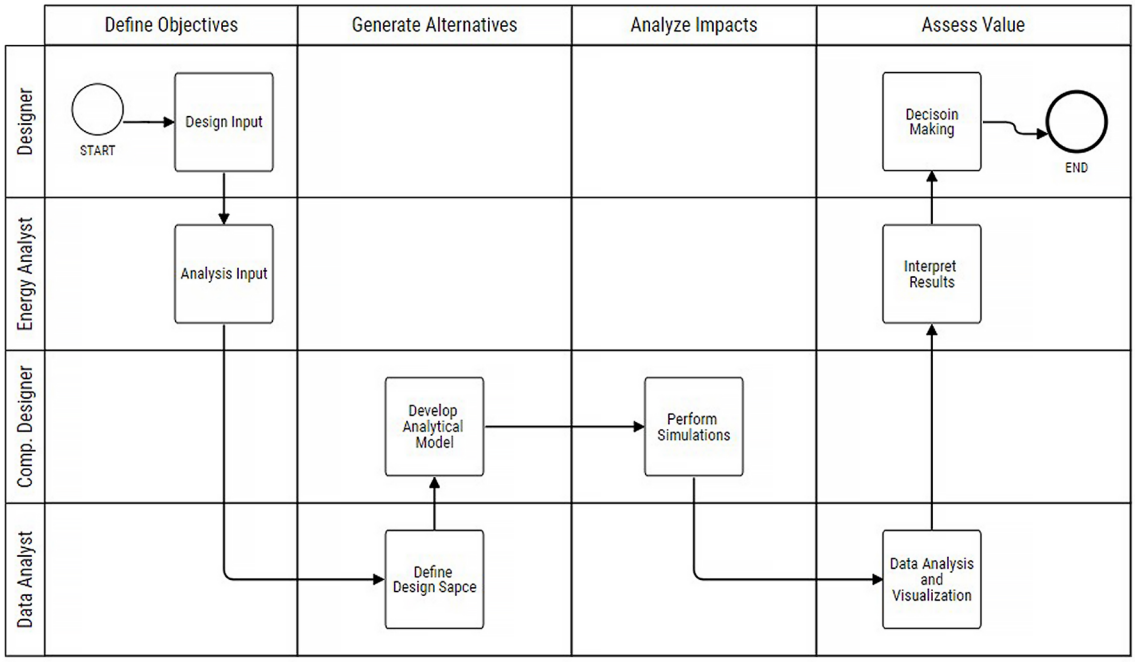


Figure 20: Students' Residence DSC process.

5.2 Objective Formulation

The objectives of the students' residence DSC were to minimize heating and cooling loads, minimize total site energy and to maximize the illuminance values. The input parameters were window to wall ratio along all facade orientations, shading device depth on all orientations, wall U-values, roof U-values, window U-values and window SHGC values (Figure 22).

5.3 Alternative Generation

Since the students' residence DSC involved three distinct analytical models, it was necessary to combine the analysis into one dataset for comparison purposes. The team achieved this by using identical input parameters for each analytical model and distinguishing the alternatives by an ID parameter. Three 64 run "design of experiments" were performed, one for each design alternative. The results were combined into a single dataset for comparison purposes.

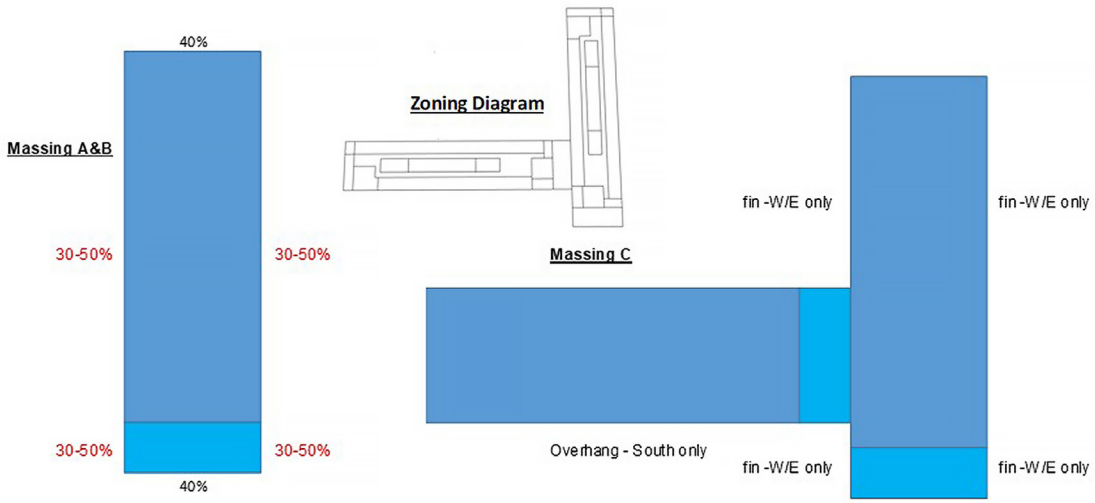


Figure 21: Students' Residence DSC massing options and zoning for DSC analysis.

Massing type	Window to wall ratio (%)	Roof Effective U value (W/m2K)	Wall Effective U value (W/m2K)	Win U (W/m2K)	SHGC(0.4,0.6)	Shades (overhang - S; fin - E,W)
A, B, C	30%, 40% 50%	0.08, 0.1, 0.15	0.1, 0.15, 0.2	0.85, 1.1	0.3,0.5,0.7	0', 1' , 2'

Figure 22: Students' Residence DSC input parameters.

5.4 Impact Analysis

In order to compare the three independent samples representing each design alternative, we used an analysis of variance (ANOVA) over the mean values of each sample. We analyzed the three samples for energy performance, as well as for both energy and daylighting. In each case, we constructed a weighted value function to capture the multi-objective value of the responses.

In the case of energy performance, the value function was computed as 0.3*Cooling Load + 0.7*Heating Load to reflect the fact that the climate is heating dominated. The ANOVA test indicated that there were no significant differences in mean energy performance between the three design options, as seen in Figure 23. This suggests that energy performance by itself could not distinguish optimal results between the options.

In the case of the multi-objective combination of energy and daylighting, the team computed the value function with all responses getting equal weight. The ANOVA test indicated that there were significant differences between the means of the samples at 90 percent confidence levels, as shown in Figure 24.

Descriptives

		N	Mean	Std Dev	Std Error	Lower Bound	Upper Bound	Min	Max
Value	A	64	60.93	12.93	1.55	57.84	64.03	33.99	83.20
	B	64	57.37	11.74	1.47	54.44	60.30	25.36	78.27
	C	64	60.03	12.09	1.51	57.01	63.05	30.49	82.75
	Total	192	59.45	12.10	0.87	57.72	61.17	25.36	83.12

Anova

		Sum of Squares	df	Mean Square	F	Sig
Value	Between Groups	439.90	2.00	219.95	1.51	0.22
	Within Groups	27547.45	189.00	145.75		
	Total	27987.34	191.00			

Figure 23: Students' Residence DSC energy performance analysis of variance.

Descriptives

		N	Mean	Std Dev	Std Error	Lower Bound	Upper Bound	Min	Max
Value	A	64	58.99	9.33	1.17	56.66	61.32	38.92	77.62
	B	64	55.52	10.63	1.33	52.87	58.18	36.90	79.33
	C	64	58.64	9.94	1.24	56.15	61.12	36.87	78.91
	Total	192	57.72	10.05	0.73	56.29	59.15	36.87	79.33

Anova

		Sum of Squares	df	Mean Square	F	Sig
Value	Between Groups	466.09	2.00	233.04	2.34	0.10
	Within Groups	18827.56	189.00	99.62		
	Total	19293.64	191.00			

Figure 24: Students' Residence DSC energy and daylighting analysis of variance.

Group Statistics					
Option		N	Mean	Std Dev	SE Mean
Value	A	64	58.99	9.33	1.17
	B	64	55.52	10.63	1.33

Independent Samples Test						
		Levene's Test for Equality of Variances				
		F	Sig	t	df	Sig (2tailed)
Value	Equal variances assumed	0.58	0.45	1.96	126.00	0.05
	Equal variances not assumed			1.96	123.92	0.05

Group Statistics					
Option		N	Mean	Std Dev	SE Mean
Value	A	64	58.99	9.33	1.17
	C	64	58.64	9.94	1.24

Independent Samples Test						
		Levene's Test for Equality of Variances				
		F	Sig	t	df	Sig (2tailed)
Value	Equal variances assumed	0.03	0.87	0.21	126.00	0.84
	Equal variances not assumed			0.21	125.51	0.84

Figure 25: Students' Residence DSC independent sample t-tests.

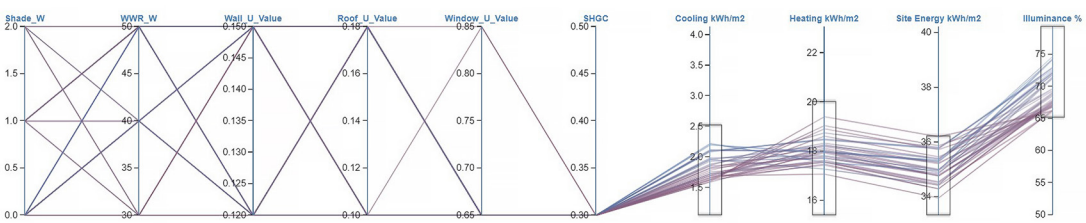


Figure 26: Students' Residence partial PCP.

In order to establish the specific differences between the samples, independent sample t-tests were used. These tests indicated that there was no significant difference between sample A and C, but there were statistically significant differences between samples A and B, as well as between sample B and C with sample B having a lower mean value function than A or B (Figure 25). This suggested that sample B was an inferior design option from a performance standpoint, while the design team would need to find other discriminators between options A and C. Figure 26 shows a parallel coordinates plot describing the alternatives and impacts in the design space.

5.5 Value Assessment

Calculating the multi-objective value function for the student's residence DSC assumed that all output parameters carried equal weight. This means the value function equation was:

Value Function = Cooling Load + Heating Load + Site Energy + Illuminance.

Part of the process of calculating value functions involves normalizing output parameters. Normalization is required because different output parameters will have different units with different scales. For a single design

alternative, the normalized value of an output parameter was calculated as:

Normalized Output Value = (Output Value – Min. Output Value) / (Max. Output Value – Min. Output Value).

However, for distinct design alternatives there is the possibility of having different maximum and minimum values for each alternative. This means that the normalization equation cannot be used to compare across alternatives. Instead, the normalized value was calculated by considering the maximum and minimum of all alternatives:

Normalized Output Value = (Output Value – Min. Output Value across Alternatives) / (Max. Output Value across Alternatives - Min. Output Value across Alternatives).

6.0 CONCLUSION

We found that although DSC has many benefits, it also has challenges that present an opportunity for further research. DSC is useful for providing decision-making support for a range of early stage design questions. Is the Passive House standard feasible for the project or not? Can we strive for higher window to wall ratios on specific facades, but still maintain a high-performance building envelope at reasonable cost? What is the optimum shading or balcony depth on each orientation of the design?

Unlike conventional building performance analysis, which relies heavily on the judgement of expert energy modelers, DSC is data driven and therefore more objective. The data serves as evidence backing up or disqualifying design preferences. This evidence-based approach increases confidence in design decision making. This in turn reduces uncertainty and allows the architect to engage more effectively with design partners, such as mechanical engineers and cost consultants.

DSC is a more accurate process than conventional building performance analysis. Evidence of this was seen with the design charrette described in Section 3. The human mind is not good at certain tasks, such as assessing the impact of multiple conflicting criteria simultaneously. We need tools like parametric analysis to assist with such determinations. Naboni et al. compared parametric analysis to conventional energy simulation[32]. They were able to identify design alternatives that reduced energy consumption for an experimental building from 98.6 kWh/m^2 (designed by conventional simulation) to 8.5 kWh/m^2 (designed by parametric analysis).

The DSC process also presents challenges. The first thing to consider is the sheer size of the *Design Spaces* formulated on real world design spaces. Fully defined *Design Spaces* will typically be of the order of magnitude of millions or billions of simulations. This is not computationally feasible. One approach to resolving this challenge is to use surrogate models such as regression, “design of experiments” or machine learning. These models reduce the amount of simulations required by learning how to accurately predict output results from a small amount of simulated data.

The second challenge arises from the need to reuse simulated data. Architectural projects, even of the same typology, tend to have significant differences in design problem formulation. This means that it is almost impossible to use simulations from one project on another even though they may have overlapping characteristics. Even within the same project, multiple alternatives or drastic changes to geometric design can require a new building performance model to be developed. This is inefficient. One possible solution is to use a technique called transfer machine learning[33]. Using machine learning as a surrogate model, we can train a reusable component of the building performance model, such as a thermal zone, and then apply this component to different projects of similar typology.

The last thing to consider is a design process problem. How does it relate to other analytical tasks including tasks undertaken by partner consultants, such as mechanical engineers and lighting designers? In order to avoid overlap and redundancy when incorporating DSC into design workflow, it is recommended to carefully process map the workflows together with all project team members.

Acknowledgments

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