INTERNATIONAL CONFERENCE ON ENGINEERING DESIGN, ICED'09
24 - 27 AUGUST 2009, STANFORD UNIVERSITY, STANFORD, CA, USA

FRAMEWORK AND METRICS FOR ASSESSING THE GUIDANCE OF DESIGN PROCESSES

Caroline M. Clevenger[1], John Haymaker[1]
(1) Stanford University, California

ABSTRACT

Traditional precedent-based architectural design explicitly generates and analyzes very few options for very few criteria. The introduction of sustainability concerns and building information modeling (BIM) to practice means professionals now have the desire and ability to generate many more options and to investigate them with respect to more criteria. Performance-based design involves the explicit definition of performance objectives for building behavior, and the systematic search through solution spaces to locate high-performing designs. As methods become available to help designers conduct performance-based design, the need and opportunity emerges for metrics to help describe, measure, and compare design processes. Through literature review and industry observations, this paper synthesizes a framework and set of metrics to assess design processes. We apply these metrics to real-world design, compare results, and discuss the strengths and weaknesses of the metric set proposed.

Keywords: Metrics, Design Guidance, Design Space, Objective Space, Solution Space, Multidisciplinary Decision-making, Sustainable Building

1 INTRODUCTION

Managing and reducing the environmental impacts of buildings has become a priority of building stakeholders and the architecture, engineering and construction (AEC) community. For example, the American Institute of Architects (AIA) in the 2030 Challenge [1] and the Federal Government in the Energy Independence and Security Act [2] both call for 0% estimated net annual fossil fuel energy consumption for new building designs by the year 2030. Maximizing building performance embodies challenges common to performance-based design in general: *complex multi-criteria problems involve a series of trade-offs which make it difficult to elicit meaningful design guidance from partial or limited analyses*. Furthermore, and by definition, promoting creativity in design practice defies full design analysis. With regard to performance criteria in general, and energy performance in particular, project teams face a daunting task to identify transcendent, high performing solutions. In this paper we first anecdotally observe the need for design guidance in energy efficient building design; next we synthesize from literature and observation a conceptual framework for performance-based design; we then propose a set of measures to assess salient characteristics of such processes; we conclude by discussing the strengths and weaknesses of our proposed metrics.

Historically, much of the AEC industry has relied on variously named precedent-based design, experienced-based design or case-based design to solve building design problems [3]. In general, precedent-based design is the process of creating a new design by combining and/or adapting previous design solutions, and benefits from tacit knowledge and lessons learned. Many AEC designers today adapt traditional precedent-based methods to meet programmatic, economic and scheduling requirements [4].

To explore the effectiveness of traditional methods in providing guidance towards energy efficiency in building design, the authors conducted a survey of 46 industry leaders averaging over 15 years of AEC experience on September 11, 2008. Among those surveyed were industry “experts”: 13 architects, averaging over 21 years of experience and 4 mechanical engineers, averaging over 26 years of experience, all working at firms of national prominence. The participation of experts in the survey is meaningful since they should be the ones with the ability to recognize underlying principles understood by industry [5]. The survey asked each practitioner to do the following:

> Consider a "typical" two story, rectangular 36,000 sf office building in a cold climate; assume an open, flat site. To the best of your ability please rank the following decisions in terms of their impact on the building in terms of a) total energy savings b) energy savings for the least first cost.

- Changes to wall construction (example 2'x4' construction vs. concrete)
- Changes to windows area (example small windows vs. large windows)
- Changes to glazing properties (example clear vs. spectrally-selective)
- Changes in Heating, Ventilation and Air Conditioning (HVAC) system type
- (example Constant Volume vs. Variable Air Volume)
- Changes to building orientation (example rotate the building on site)
- Changes to building geometry (example relatively square vs. long and rectangular)
- Changes to lighting design (upgrade efficiency for same lighting level)

Results collated with respect to industry professionals' estimates of the relative impact of a) total energy savings and b) energy savings for the least first cost showed similar patterns. Based on tacit knowledge, professionals were generally able to correctly identify the decision with the most impact (in this case, window area). However, the mean and standard deviation of estimations of the importance of remaining decisions quickly approached random guessing regardless of the cross-section of the population analyzed (Figure 1).

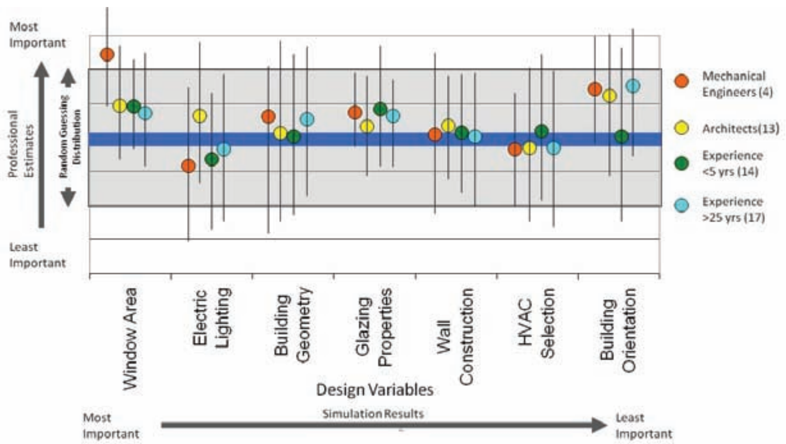

Figure 1: Survey results indicating a lack of consistency among industry professionals estimating the rank of the impact various design decisions on building energy efficiency.

In general, these survey results indicate industry professionals make highly deviant estimates about the impacts of design variables on energy efficiency across categorization by experience levels, design background or familiarity with climate. While the survey is simple and anecdotal, results are consistent with other research that suggests without additional resources, professionals lack the tacit understanding necessary to guide energy efficient decision-making in specific design projects [6]. Many researchers agree that building science underlying whole building performance is a complex, "wicked problem" that presents many challenges to modeling and rationalization in theory and in practice [7]. To maximize whole building performance designers must be able to understand and successfully model stochastic, dynamic, continuous event-based systems [8], and limits exist which bound human capacity to intuit such systems [9].

Design, in general, is the process by which a designer develops and/or selects the means to achieve a set of objectives, subject to a set of constraints; and a design object is a satisfactory solution to this problem [10]. Performance-based design, in specific, is a process in which a design team develops performance goals and generates and analyzes options in order to seek high performing solutions [11]. In performance-based design, we define design guidance as the measurable and replicable impact of a design process in the determination (generation and selection) of design solutions. Today, sustainability frameworks like LEED increase the number of explicit goals designers are asked to consider [12]. Building information modeling (BIM), parametric modeling and various automation and search algorithms expand by orders of magnitude the number of options that it is possible to analyze within a reasonable amount of time. Advanced energy analysis techniques integrate these emerging tools with existing building energy performance (BEP) simulation software and provide the opportunity to access computer analysis and experiment techniques, successfully used in other engineering disciplines, for high performance building design. These opportunities raise the question, which techniques or strategies will be the most useful in generating higher performing solutions? The contribution of this paper is the synthesis of a literature and observation-based framework for performance-based design and the development of a correlated set of metrics to allow the measurement and comparison of design processes. The emphasis is the development of a useful set of metrics, rather than the validity of individual metrics or specific case study results.

2 OBJECTIVE SPACE, DESIGN SPACE, IMPACT SPACE, AND SOLUTION SPACE

In this section, we synthesize definitions for Objective Space, Design Space, Impact Space, and Solution Space to describe performance-based design and support the development of our design process metrics. Figure 2 illustrates these concepts and their relationships.

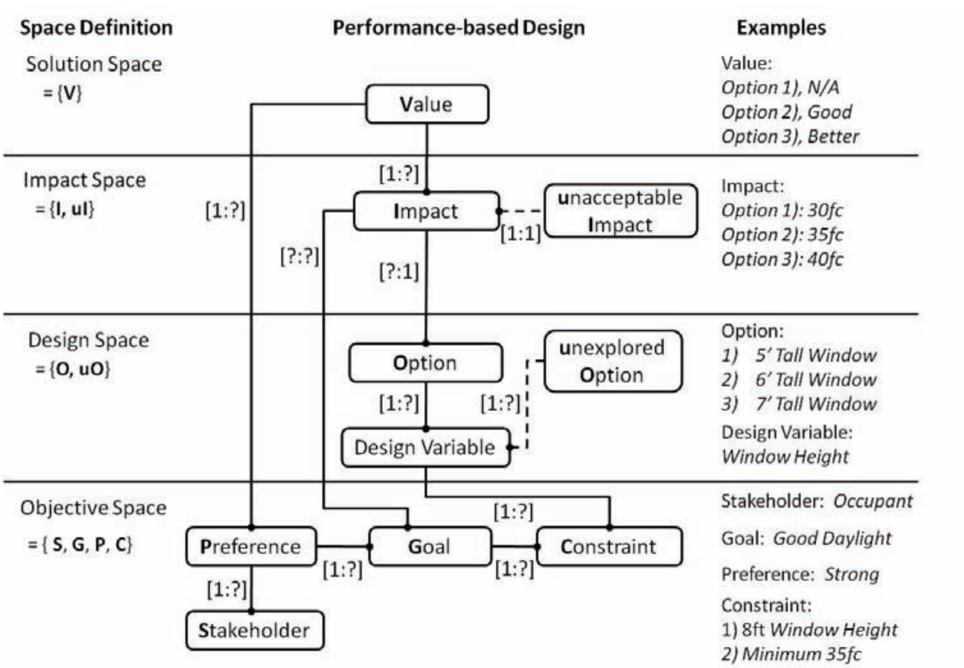

Figure 2: Process Map for Performance-based Design [13]

OBJECTIVE SPACE = { S, G, P, C }

Objective Space consists of the set of stakeholders, goals, preferences and constraints for a project. Stakeholders are interested parties. Goals are declarations that establish the intended properties of design solution(s) [14]. Preferences are the expressed valuations of the goals by stakeholders [15]. Constraints limit goal or design variable ranges and domains. Constraints define feasibility for design options or acceptability for design solutions. Goals, preferences and constraints are inter-related since weights and acceptable ranges of performance can never be completely separate [16].

DESIGN SPACE = { O, uO }

Design Space consists of the set of all possible design options that meet the design constraints, whether explored and unexplored [10]. A design option is defined as a unique combination of design variables. Design variables represent individual decisions to be made by the designer. These variables are frequently discrete, but can also be continuous in building design (i.e, building length). Currently, our framework does not distinguish an hierarchy among design variables. In general, Design Space is sufficiently vast that it can be thought of effectively unbounded relative to designer's time and reasoning ability [17].

IMPACT SPACE = { I, uI }

Impact Space consists of all calculated impacts for design options relative to project goals, whether acceptable or unacceptable. Constraints placed on goals determined the acceptability of the assessed performance prospect. Performance prospects are analysis or simulation estimations of a future condition ranging from relatively quick and simple to elaborate and detailed [16]. These estimates may or may not be easily quantifiable. When possible, we evaluate performance prospects in units of dollars believing dollars to be the most common and transportable unit. When cost estimates are not available or analyses are more subjective and/or less detailed, it may be necessary to adopt other units for performance (e.g., +3, -3). Consistency rather than precision should be stressed for comparison.

SOLUTION SPACE = { V }

Solution Space consists of the set of design values generated. Design value is a function of an option's impact and stakeholder preference relative to the goal(s) evaluated. Uncertainty is currently not considered in the Solution Space nor the overall framework. We leave more advanced concepts such as utility and portfolios for later research and focus here only on "value-centric" solutions [18].

Prior research has characterized design as the co-evolution of the problem space and solution space, or identified problem redefinition as the foundation of creativity leading to greatest design value [19] [20] [21]. We acknowledge our framework must be dynamic, and the relationship between the four spaces iterative, emergent and time-dependent. For example, determination of value may cause a designer to revise either project goals or constraints or both, thus changing the target range of performance. In the next section, we use this framework as the basis of development for design process metrics. We then use these metrics to compare design guidance provided by two different design processes on a real-world case study.

3 DESIGN PROCESS METRICS

The framework of performance-based design developed in the previous section, characterizes performance-based design as the exploration of a Design Space with the goal of maximizing value. The metrics we propose are intended to serve as set of numerical characterizations of this process. Metrics have generally proven elusive for design processes [22], [23]. Rigorous "quality indicators" have been explored to mathematically compare and assess approximations of pareto-optimal fronts. However, innovative design processes tend to defy characterization as objective mathematical search. Shah et al, have used the metrics quantity, variety, quality, and novelty to evaluate idea generation, proposing these metrics represent how well a design method expands Design Space, and how well a design method explores Design Space [24]. Simpson et al, define the metrics design knowledge and design freedom to improve design process flexibility [25]. Design knowledge relates directly to information certainty, the decisiveness of a design variable input. Design freedom is characterized by the overlap of the target range of performance and the feasible range of performance. In their current state, however, these metrics are not sufficient or fully suitable for our framework of performance-based design. Quantity, for example, is no longer a meaningful gauge for automated computer search. Design freedom, although critical, may not serve as a useful indicator if the feasible range of performance remains unknown, as is frequently the case with "wicked problems" in general, and building energy performance in particular. Here we modify, adapt and expand existing metrics and common mathematical measures to describe performance-based design. We then test the usefulness of these proposed metrics in a real-world case study.

3.1 Terms

To begin, we identify the following list of terms:

Table 1: Terms

n, the number of design variables in a Design Space. $n_{trade\text{-}off,}$ the number of design variables resulting in challenging impacts relative to competing goals c_i, the number of elements (choices) for design variable, n_j. For design variables with large or infinite (continuous variable) number of alternatives, c_i is defined by the analysis performed (i.e., how many alternatives were assigned to the variable in the model or simulation). F, the total number of feasible design options (combinations) for n design variables, (e.g.; $C = c_1 \times c_2 \times c_3 \times \ldots c_n$). If dependencies or hierarchies exist, C may differ. O, the number of design options generated that meet the design constraints ($O \leq F$). uO, the number of unexplored design options that meet the design constraints ($uO = F - O$). G, the number of goals analyzed in the Impact Space. $p_1, \ldots, p_g$, preference relative to each goal analyzed. r1, . . . , rg, rationality of each design goal analyzed. (See Objective Space Quality.) t, total time required to generate and analyze all design options. S, the number of solutions generated; design options analyzed whose performance prospect(s) meets or exceeds performance requirements, ($s \leq d$). $pp_{11}, \ldots, pp_{ij}$, performance prospect (calculated impact) of a design option, o_i relative to each goal analyzed, g_j. $v_1, \ldots, v_s$, design value assessed for each design solution s_i; (e.g.; $v_i = pp_{i1} \times p_1 + \ldots + pp_{ig} \times p_g$.).

3.2 Metrics

Using the terms listed in Table 1, we propose the following eight metrics as useful for evaluation and comparison of performance-based design. We partition these process metrics into three categories: problem comprehensiveness, solving efficiency, and solution quality. We illustrate the metrics using a real-world example and then discuss their strengths and weaknesses.

Problem Comprehensiveness

OBJECTIVE SPACE QUALITY, $OSQ = \sum p_i r_i / G$

Objective Space Quality is the sum of stakeholder preference multiplied by rationality for all individual goals divided by the total number of goals analyzed. Preference is established through formal preference elicitation [26] [27], or normalized and equally distributed among goals. Building on definitions of rationality from [28] [4], we characterize goal rationality by assessing the manner in which the goals were created. We use the following values for goal rationality coefficients:

- Fully integrated project goals made collectively by all stakeholders = 1
- Aggregation of stakeholder goals independently generated =.75
- Small group of individuals setting project goals =.5
- Individual stakeholder setting project goal(s) = .25

IMPACT SPACE COMPLEXITY, $ISC = n_{TRADE\text{-}OFFS} / n$

Complexity is the number of design variables found to result in performance trade-offs (challenging impacts) divided by total number of design variables. An impact is challenged by another when a change to a decision variable results in an inverse relationship of performance prospects relative to two or more goals.

Solving Efficiency

DESIGN SPACE SAMPLING, DSS = O / (O + uO) = O / F

Design Space Sampling is the number of design options generated relative to the total number of feasible design options. It is a measure of the percentage of the Design Space explored. If iteration results in changes to goals and/or constraints (a redefinition of target performance, or option acceptability), Design Space Sampling is revised to include the expanding number of explored and unexplored options i.e.; *DDS = O' / (O' + uO')*.

RATE OF IMPROVEMENT, ROI = (MAX(v_i) – MIN(v_i)) / O

Rate of Improvement is the range of value in the Solution Space divided by the number of options generated and analyzed.

AVERAGE ITERATION TIME, AIT = t / O

Average Iteration Time is the average time to generate an option and analyze its impact(s) [29]. A discrete iteration occurs once the impact(s) have been assessed for an option.

Solution Quality

TOP VALUE ANALYZED, TVA = MAX(v_i)

Top Value Analyzed is the value of the top performing solution. It is possible to have multiple solutions with TVA.

AVERAGE VALUE ANALYZED, AVA = $\sum v_i$ / S

Average Value Analyzed is the average design value of all solutions analyzed. If the top value feasible (TVF) is known, it is possible to normalize both **TVA** and **AVA** to the TVF value.

AVERAGE VALUE DISTRIBUTION, AVD = $\sum$*(AVA - v_i) / S*

Average Value Distribution is the standard deviation of the design values for all solutions generated.

4 INDUSTRY CASE STUDY

Our case studies examines a professional energy analysis performed during schematic design of a 338,880 sf Federal Building with 10 floors and a parking sub-basement sited in a mixed (hot cold), and dry climate at an elevation of 4,220ft. Design analysis occurred over a period of 27 months. At the beginning of the project, the client set an annual energy usage target of 55 kBtu/sf/yr for the project, but did not make this performance level a project constraint. In our assessment we use prescriptive energy code minimums as the constraints to determine the performance requirements of a solution.

Professional Exploration

Results from a total of 13 energy simulation runs were generated during 4 rounds of energy modeling over a 3-year period, and represents a real-world design exploration as preformed in industry today. Table 2 lists the design variables analyzed. Table 3 lists the individual building energy performance (BEP) simulations performed and the estimates of annual energy consumption (kBTU/sf/yr) provided to the project team.

Table 2: Design Variables and Choices explored in Professional Energy Analysis.

Design Variables	**Choices**		
	Final Schematic Design	Additional Alternatives	ASHRAE Baseline
Building Geometry	A	B, C	A
Windows	U-value: 0.30; SC: 0.44; SHCG: 0.378		U-value: 0.57; SC: 0.57; SHCG: 0.49
Roof	U-value: 0.33		U-value: 0.65
Wall Above Grade	U-value: 0.083		U-value: 0.113
Wall Below Grad	U-value: 0.056		U-value: 0.1
Glass on Exterior	95%		40%
Exterior with Shading	50%	38%	0%
Electric Lighting	1.10 w/sf		1.22 w/sf
Daylight Sensors	Yes		No
HVAC	B: High efficiency, Heat recovery Outside air minimum: 10%	A, C	B: Standard Efficiency, Outside air minimum: 20%

Table 3: BEP Simulations and Results from Professional Energy Analysis

Option	Option Name	Results (kBtu/s yr)
1.1	Scheme A	61.2
1.2	Scheme B	58.2
1.3	Scheme C	56.1
2.1	Scheme A + Better Materials	67.5
2.2	Scheme A + Better Materials + Efficient Lighting	66.2
2.3	Scheme A + Better Materials + Efficient Lighting + Daylighting	64.1
2.3.1	Scheme A + Better Materials + Efficient Lighting + Daylighting + Mechanical Scenario A	57.8
2.3.2	Scheme A + Better Materials + Efficient Lighting + Daylighting + Mechanical Scenario B	55.8
2.3.3	Scheme A + Better Materials + Efficient Lighting + Daylighting + Mechanical Scenario C	57.3
3.1	ASHRAE BASELINE: Scheme A + Efficient Lighting + Daylighting + Mechanical Scenario B (40% Glass)	58.8
3.2	Scheme A + Better Materials + Efficient Lighting + Daylighting + Mechanical Scenario B (95% Glass)	53.2
3.3	Scheme A + Better Materials + Efficient Lighting + Daylighting + Mechanical Scenario B (95% Glass, 50% Shading)	46.8
4.1	Scheme A + Better Materials + Efficient Lighting + Daylighting + Mechanical Scenario B (Revised population, Revised schedules, 95% Glass, 38% Shading)	48.2

Applying the terms defined by our metrics to this professional energy analysis, we assess the following:

Table 4: Terms evaluated for Professional Analysis

Terms	n	$c_1,c_2,c_3 \ldots c_{10}$	C	O	G	t	S	$pp_{1energyUsage}$ [2]	$p_{1energyUsage}$	$v_{solution1}$, $v_{solution2}$ [2]
	10	3,2,2,2,2, 2,3,2,2,3	3 x 2 x 2 x 2 x 2 x 2 x 3 x 2 x 2 x 3 = 3456	13	1[1]	27 mo.	3	1	N/A	$v_{3.2}$ = \$336,00 $v_{3.3}$ = \$720,60 $v_{4.1}$ = \$636,60

1 Energy usage. Although aesthetics influenced early decisions, analysis for aesthetics were beyond the scope of the design analysis performed.
2 Performance prospects were calculated using project assumptions regarding costs of energy in NPV (20 years, 3% interest rate) relative to minimum code requirement (model run 3.1)).

New Exploration

Researchers at Stanford University are leading efforts to develop a suite of new technologies and methodologies in support of multidisciplinary design, analysis and optimization [29]. This strategy uses Process Integration and Design Optimization (PIDO) tools as a platform for analysis management using existing AEC analysis tools. In the new exploration, we used PIDO to apply a Design of Experiment exploration to evaluate design trade-offs between 1) first cost, 2) energy usage 3) thermal comfort for the Federal Building case study. Table 5 lists the design variables used in the advanced energy analysis performed.

Table 5: Design Variables and choices explored in Advanced Energy Analysis

Design Variables	Choices	
Building Geometry	Square (100ft x 100ft)	Rectangular (200ft x 50ft)
Building Orientation	-90, -45, 0, 45, 90	
Window Construction	U-value: 0.30 SC: 0.44 SHCG: 0.378	U-value: 0.57 SC: 0.57 SHCG: 0.49
Exterior Wall	U-value: 0.083	U-value: 0.113
Percent Glass on Exterior	95%	40%
Percent Exterior Shading	50%	0%
Electric Lighting	1.10 w/sf	1.22 w/sf
Daylight Sensors	Yes	No
HVAC	High efficiency, Heat recovery, Outside air minimum: 10%	Standard Efficiency, Outside air minimum: 20%

Applying the terms defined by our metrics to this research-based, advanced energy analysis, we assess the following:

Table 6: Terms evaluated for Advanced Analysis

Terms	n	c1,c2,c3 . . . c9	C	O	G	t	S	$pp_{energyUsage}$ [2]; $pp_{firstCost}$; $pp_{thermalComfort}$	$p_{energyUsage}$ $p_{firstCost}$ $p_{thermalComfort}$	$v_{solution1}$, $v_{solution2}$ [2]
	9	2,5,2,2,2 ,2,3,2,2	2 x 5 x 2 x 2 x 2 x 2 x 3 x 2 x 2= 1280	128 0	3[1]	1 day	3	PIDO generated results	.33; .33; .33	PIDO generate results

1 Energy usage (minimize), first cost (minimize), hours outside thermal comfort zone (minimize).
2 Performance prospects were calculated using project assumptions regarding costs of energy in NPV (20 years, 3% interest rate) relative to minimum code requirement (model run 3.1)).

Applying our metrics to both the professional energy analysis and a research-based advanced energy analysis, we evaluate and compare the two design explorations in Table 7:

Table 7: Metrics evaluated for Traditional and Advanced Analysis

Metrics	OSQ	DSS	ISC	TVA[2]	AVA	AVD	ROI	AIT
Traditional Analysis	.125[1]	13 / 3456	0 / 1	$720,600	$564,400	$165,100	$29,580	2.1 mo.
Advanced Analysis	.165[2]	1280/1280	3 / 9	$998,400	$669,400	$398,060	$625	1.1 min.

[1] 1* .25 / 2 = .125
[2] (.33* .5) + (.33* .5) + (.33* .5) / 3 = .165

4.1 Discussion

After illustrating these metrics with an example, we will make preliminary observations and briefly discuss the strengths and weaknesses of the proposed metrics. First, with the exception of AIT, the metrics are to be maximized. The advanced energy analysis scored higher than the traditional (professional) energy analysis across all metrics with the exception of the Rate of Improvement (ROI). This deficit is easily offset, however, by the vast reduction in iteration time; and the performance improvement achieved using the traditional analysis technique in 2.1 mo., in theory, could be achieved using the advance analysis techniques in approximately one hour. In general, we observe that the proposed metrics are not independent, but similar to Shah et al [24] we believe that each metric captures a unique aspect of performance-based design and do not question their dependence.

While Design Space Sampling, DSS serves as an indicator of the percent of the Design Space analyzed, it says nothing of the distribution of this sampling. As a direct function of the number of options, however, DSS “encourages mistakes” by rewarding all design options not just the ones that result acceptable solutions. Research has shown that, in general, generating more options increases the chance of better performance [30]. Since DSS is inversely proportional to F, the theoretical limit of all feasible design options, it potentially encourages over-constraint of the Design Space. This hazard, however, is balanced by solution quality metrics intended to penalize an over-constrained Design Space.

At first glance, performance-based design Top Value Analyzed (TVA) may appear to many to be the exclusive metric for determining the usefulness of a design process regardless of the number of options generated. In other words, whether a designer generates only one design, 1000 diverse designs or 100 similar designs, may be insignificant if the Solution Space contains solution(s) with highest value. However, other research has shown that TPV is a reliable measure of design process only when a Design Space is finite (completely defined) and an Impact Space fully computable. In such spaces, search is a good model of design [17]. For problems that are ill-defined and/or non-computable, research has shown optimization and other multi-criteria process models may force premature judgments and identify only local maximum(s) while leaving solutions with highest value unidentified [5]. As a result, we include the metrics TVA, AVA, and AVD to evaluate solution quality, but intend to further examine additional process and outcome indicators in the future. At a minimum, AVA and AVD represent statistical concepts commonly used to describe sets of data. In combination, these measures are intended to assess whether the analysis performed focused on high impact design variables. Presumably if analysis examines design variable to which overall performance is highly sensitive, there will be a high standard deviation. If those design variables are then appropriately tuned, it will result in a high average value analyzed, AVA. A potential weakness of these metrics is that for small data sets (e.g., few analyzed options in real-world projects), these metrics will have limited significance.

Finally, Analysis Space Rate of Improvement, ROI measures the average incremental improvement of the analyses performed. This is intended to serve as an indicator of the efficiency of the exploration because it is a function of both how sensitive performance is to the design variables analyzed and how much learning occurs from the analyses performed. The metric's strength is that it prevents falsifying or "gaming" improvement by starting from an unfairly low baseline since only viable solutions are included in the range. Its weakness is that it does not reflect the sequence of the decisions made and gains made at the beginning or end of the exploration are assessed equally.

5 CONCLUSION

AEC professionals today seek processes to help them identify high performing solutions. Growing numbers of competing objectives and sophisticated analyses have increased the complexity of design problems for buildings. Precedent-based design and/or narrow applications of BEP currently dominate in practice. A simple survey intended to measure industry professionals' tacit knowledge of the drivers of building energy performance showed a lack of common understanding. Without basic understanding of such design principles even among building experts, significant opportunity exists for analyses to aid performance-based design. It is important, therefore, to be able to compare and evaluate the effectiveness of various design processes to provide this guidance. Literature review provides a foundation but not a complete theoretical framework to characterize performance-based design assisted by advanced computer and analysis capabilities. In this paper, we synthesize a framework and propose metrics that may be useful measures. Potential strengths and weaknesses are discussed. A real-world case study of professional energy analysis is used to illustrate the metrics, demonstrating concrete and numeric assessments of an actual project. The contributions are the proposed framework and metric set to support comparison and evaluation of problem comprehensiveness, solving efficiency, and solution quality for existing or emerging design processes.

REFERENCES

[1] American Institute of Architects, "National Association of Counties Adopts AIA Challenge of Carbon Neutral Public Buildings by 2030," press release July 30, 2007.

[2] Federal Energy Management Program (FEMP). P.L. 110-140 (H.R.6.) Energy Independence And Security Act (EISA) of 2007.

[3] Watson, I., Perera, R. Case-Based Design: a Review and Analysis of Building Design Applications. *Journal of Artificial Intelligence for engineering Design, Analysis and Manufacturing AIEDAM*, 1997, Vol. 11, No. 1, pp 59-87.

[4] Chachere, J., Haymaker, J. Framework for Measuring Rationale Clarity of AEC Design Decisions, 2008, *CIFE Technical Report, TR177*, Stanford University.

[5] Cross, N. Expertise in Design: an overview, *Design Studies*, 2004, Vol. 25, No. 5, pp. 427-441.

[6] Papamichael, K., LaPorta, J., and Chauvert, H. Building Design Advisor: automated integration of multiple simulation tools. *Automation in Construction*, 1998, 6 4 pp. 341–352.

[7] Cross, R., Roozenburg, N. Modelling the Design Process in Engineering and Architecture, *Journal of Engineering Design*, Vol. 3, No 4, 1992.

[8] Bazjanac, V. Building Energy Performance Simulation Presentation, 2006. Lawrence Berkley National Laboratory, University of California, VVT Technical Research Centre of Finland.

[9] Papamichael, K., Protzen, J.P. The limits of intelligence in design. *Proceedings of the Focus Symposium on Computer-Assisted Building Design Systems 4th International Symposium on Systems Research, Informatics and Cybernetics*, 1993, Baden-Baden, Germany.

[10] Tate D, Nordlund M., A design process roadmap as a general tool for structuring and supporting design activities. *SDPS J Integrated Design and Process*, 1998, Sc 2(3):11–19.

[11] Deru, M., Torcellini, P.A. Improving Sustainability of Buildings Through a Performance-Based Design Approach. 2004 *Preprint, National Renewable Energy Laboratory (NREL) NREL/CP-550-36276*.

[12] US Green Building Council, LEED (Buildings: Leadership in Energy and Environmental Design), Environmental Building rating System Criteria, 1996.

[13] ISO 10303-11:2004 Industrial automation systems and integration -- Product data representation and exchange -- Part 11: Description methods: The EXPRESS language reference manual.

[14] Lamsweerde, A., Goal-Oriented Requirements Engineering: A Guided Tour. *Proceedings RE'01, 5th IEEE International Symposium on Requirements Engineering,* Toronto, 249-263.

[15] Payne, J., Bettman, J., Schkade, D. Measuring Constructed Preferences: Towards a Building Code. *Journal of Risk and Uncertainty*, December, 1999, Vol 19, Numbers 1-3.
[16] Earl C., Johnson J. and Eckert C 'Complexity', Chapter 7 in Design Process Improvement - a review of current practice, 2005, Springer.
[17] Kotonya G, Sommerville I. Requirements engineering: processes and techniques, 1997 (Wiley, Chichester).
[18] Ross, A. M., Hastings, D. E., Warmkessel, J. M., and Diller, N. P.,Multi-Attribute Tradespace Exploration as Front End for Effective Space System Design, 2004, Journal of Spacecraft and Rockets, Vol. 41, No. 1.
[19] Dorst, K and Cross, N., Creativity in the Design Process: co-evolution of problem-solution, *Design Studies*, 2001, 22 pp 425-437.
[20] Maher, M. L., Poon, J., Boulanger, S., Formalising Design Exploration As Co-Evolution: A Combined Gene Approach, Advances in Formal Design Methods for CAD, 1996,(Gero, J S and Sudweeks, F eds.), Chapman and Hall, London, UK.
[21] Gero, J S, Creativity, emergence and evolution in design. *Knowledge-Based Systems*, 1996, Vol 9, pp. 435–448.
[22] Briand, L., Morasca, S., Basili, V., Defining and validating high-level design metrics, University of Maryland at College Park, College Park, MD, 1994.
[23] Bashir, H. A., and Thompson, V. Metrics for design projects: a review. Design Studies, 1997, 20(3), 163-277.
[24] Shah, J., Vargas-Hernandez, N., and Smith, S., Metrics for Measuring Ideation Effectiveness, *Design Studies*, 2003, Vol. 24, No. 2, pp. 111–134.
[25] Simpson, T., Rosen, D., Allen, JK, Mistree, Farrokh, Metrics for Assessing Design Freedom and Information Certainty in the Early Stages of Design, *Proceeding of the 1996 ASME Design Engineering Technical Conferences and Computers in Engineering Conference*, August `8-22, 1996, Irvine California.
[26] Haymaker J., Communicating, Integrating, and Improving Multidisciplinary Design Narratives, *International Conference on Design Computing and Cognition*, 2006, 635-653 (Springer, Netherlands).
[27] Ross, A. Multi-Attribute Tradespace Exploration with Concurrent Design as a Value-Centric Framework for Space System Architecture and Design. Dual-SM, Massachusetts Institute of Technology, 2003.
[28] Edvardsson E. and Hansson S.O. (2005). 'When is a goal rational?'. Social Choice and Welfare 24: 343–36.
[29] Smith, R., Eppinger, R., A predictive model of sequential iteration in engineering design, Management Science 43 (8) (1997).
[30] Flager, F., Soremekun, G, Welle, B., John Haymaker, J., Bansal, P., Multidisciplinary Process Integration and Design Optimization of a Classroom Building, CIFE Technical Report #TR175 October 2008.

Contact: C.M. Clevenger
Stanford University
Department of Civil and Environmental Engineering
473 Via Ortega, Room 292
Stanford, CA 94305-4020
USA
Phone: 650 723-4945
Fax: 650 723-4806
E-mail: cclevenger@stanford.edu

Caroline is a PhD candidate in Civil and Environmental Engineering at Stanford University. With her advisor, John Haymaker her doctoral research focuses on design guidance to promote the design of higher performing, more energy efficient buildings. She has academic degrees and several years of practical experience in sustainable design and energy modeling. Her research is funded by Stanford's Precourt Energy Efficiency Center (PEEC) and performed in association with Stanford's Center for Integrated Facility Engineering (CIFE).