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The Value of Design Strategies Applied to Energy Efficiency

By

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Abstract
Today, advanced design strategies supported by iterative engineering performance calculations expand the number of alternatives designers can analyze by orders of magnitude. Yet, in the face of vast, under-constrained design challenges with wide ranging and often-subjective implications, it is not possible to replace building design with automated search. Saddled with limited time and resources, building designers are left to choose among strategies of varying costs and capabilities to assist in the generation and selection of alternatives. Designers require assistance in the selection of strategies that are effective in promoting sustainability.

This paper develops a method to compare the value of distinct design strategies. Using the Design Exploration Assessment Methodology (DEAM), the paper demonstrates that designers face non-trivially distinct challenges, even in the well-defined arena of design for energy efficiency. It evaluates and compares the effectiveness of strategies such as point-analysis, screening, trend analysis, and optimization, identifies associated process costs, and presents a method to assess the relative value of information that each strategy provides for a given challenge. Findings empirically rank six strategies for two challenges and demonstrate the relatively high value of trend analysis for energy-efficient design. The implication is that advanced computer analysis strategies should be pursued to support high performance design and motivates future research to assess value of various strategies in the context of broader and often more qualitative fields of sustainable design.

Keywords
High Performance, Energy Efficiency, Strategy, Challenge, Value

Classification:
Conceptual Paper

Terms
<u>Components</u>
- *Variable*: a design choice to be made. A *variable* can be discreet (i.e., number of windows) or continuous (i.e., building length).
- *Option*: individual *variable* input(s) (i.e., number of windows = {1, 2, or 3}; building length = 10-20 meters).
- *Decision*: the selection of an *option* (i.e., a number of windows = 2; building length = 12.75 meters).
- *Alternative*: a combination of *decisions* about *options*.
- *Stakeholder*: a party with a stake in the selection of *alternatives*.
- *Goal*: declaration of intended properties of *alternatives*.
- *Preference*: weight assigned to a *goal* by a *stakeholder*.
- *Constraint*: limit placed on *options*.
- *Impact*: *alternative's* estimated performance according to a specified *goal*.
- *Requirement:* limit placed on *impacts.*
- *Objective*: union of *stakeholders*, *goals*, *preferences* and *constraints*.
- *Value*: net performance of an *alternative* relative to all *objectives.*

<u>Dimensions</u>
- *Challenge*: a set of *decisions* to be made ranging from simple to complex.
- *Strategy*: a procedure to generate *decisions* ranging from none to advanced.
- *Exploration*: a history of *decisions* made ranging from misled to guided.
- *Design Process*: implementation of a *strategy* to a *challenge* resulting in an *exploration*.

Guidance: variation in *exploration* produced by applying different *strategies* to a given *challenge*.

Spaces

Objective space: set of *stakeholders, goals, preferences* and *constraints.*

Alternative space: feasible (explored or unexplored) *alternative*s for a given *challenge*.

Impact space: analyzed *impacts* of *alternative*s relative to *goals*, determined to be acceptable or unacceptable according to *requirements*.

Value space: *values* of the set of *alternatives* generated during an *exploration*.

Design space: the space consisting of *objective, alternative, impact and value spaces*.

Challenge Metrics

Objective space size (OSS): the number of *objectives* considered in the *challenge*.

Alternative space interdependence (ASI) - the number of first order interactions among *variables* divided by total number of *variable* combinations. ASI represents the extent to which interactive effects impact *value.* In the synthetic experiment performed for this research, it is calculated using built-in capabilities of existing process integration design optimization (PIDO) software. In general, the higher the ASI is, the more complex the *challenge*.

Impact space complexity (ISC): the number of *variables* found to result in performance trade-offs (divergent *impacts*) divided by total number of *variables*. ISC represents the percentage of *variables* with competing *objectives*. In the synthetic experiment performed for this research, ISC is observable using built-in capabilities of existing PIDO software. The higher the ISC is, the more complex the *challenge*.

Value space dominance (VSD): the extent to which *value* is dominated by individual *variables* calculated using sensitivity analyses. VSD represents the importance of individual design *decisions*. In the synthetic experiment performed for this research, it is calculated using built-in capabilities of existing PIDO software. Because the lower the VSD, the more complex the *challenge*, VSD is presented as its reciprocal (1-importance).

Strategy Metrics

Process Cost (PC): the estimated cost of implementing a *strategy*; the estimated number of hours required, multiplied by an assumed labor rate ($100/hr).

Value of Information: difference between expected project *value* with the information, and expected project *value* without the information, minus the *process cost* of acquiring the information.

Exploration Metrics

Value space maximum (VSM): the top *value* calculated for *alternatives* generated in a given *exploration*. This metric characterizes the maximum *value* generated.

For additional background information describing these metrics and terminology see (Clevenger & Haymaker, 2011). We use italics throughout this paper to indicate explicit reference to these definitions.

Introduction

Design is a sequence of events in which a problem is understood, and *alternatives* are generated and evaluated (Cross & Roozenburg, 1992), (Frost, 1992), (Clarkson & Eckert, 2005). Performance-based or high performance design involves selection of *variables* to address formal performance *objectives* (Zhu & Kazmer, 2000), (Foschi, et al. 2002). Performance-based design seeks to maximize *value* according to *challenge* addressed, by implementing a *strategy* that leads to effective *exploration* (Clevenger & Haymaker, 2010). In this paper, we examine high performance design with energy efficiency as the *objective*. Today, owner, contractual and user demands in Architecture, Engineering and Construction (AEC) industries increasingly address a wider variety of *objectives*. Designers are increasingly asked to reliably maximize the *value* of their buildings with respect to multiple sustainability *objectives* (AIA, 2007) including occupant comfort and health, and many other social, environmental, and economic performance considerations.

Computer modeling automation promises powerful assistance for estimating building operational costs by applying a given *strategy* to a given *challenge*. In building energy performance research, computer analyses that perform building optimization (Wetter, 2004), (Christensen et al, 2006), trade-space analysis (Ross & Hastings, 2005) and Process Integration Design Optimization (Flager et al, 2009) (Welle et al, 2011) are being tested. Such advanced computing *strategies* provide capabilities well beyond those of unaided humans, and significantly extend designers' ability to search large design spaces (Woodbury & Burrow, 2006).

To date, however, designers have met with relatively modest success in leveraging computer analysis to meet sustainability *objectives* and have struggled to reliably improve building operational performance. Flawed or inaccurate models, in part, result from the inherent and acknowledged complexity of building science. Example deficiencies range from difficulty predicting solar radiation (Gueymard, 2009) to lack of consistency in modeling building thermal performance etc. (Crawley et al, 2008) to name a few. Additional barriers to the fidelity of computer analysis include the significant time needed to prepare models, inaccuracies within the models, and the vast number of inputs and output estimates that are themselves inconsistent and highly dependent on various assumptions (Majidi & Bauer 1995), (Clarke, 2001), (Bazjanac, 2008). While such deficiencies can plague high performance energy-efficient design, they expand in the face of the broader field of sustainable development which includes more nebulous *objectives* such as ethics, health and comfort in decision making (Williamson et al, 2003) (Wilson et al, 2007). Researchers have suggested that systems-thinking is necessary to identify complementary performance tools that advance sustainable development (Robert et al, 2002). Broader evaluations, however, tend to lack clear identification, definition or ability to evaluate precise metrics. In general, designers are frequently hesitant to apply unfamiliar *strategies* because they are unable to assess the *value* provided. In high performance building, design teams frequently limit the role of energy modeling in professional practice to performance verification near the end of a design process. Moreover, to date, such analyses generally fail to reliably support performance-based design *explorations* or accurately predict building performance (Papamichael & Pal, 2002), (de Wilde & van der Voorden, 2004), (Hensen, 2004). However, despite these difficulties, computer simulation is having significant and growing impact on building delivery processes (McGraw Hill, 2007), and is being used to support a growing number of performance objectives (Fischer, 2006). Designers are now faced with needing to choose from these growing lists of strategies, one that is best suited to their specific challenges.

This paper focuses on energy efficient design as an important sub-set of sustainable design. It does not address the fidelity of building performance modeling assumptions or algorithms, but leaves such research to others (Willman, 1985), (Judkoff & Neymark, 1995), (Crawley et al., 2001). Several researchers have also examined the role of uncertainty in energy modeling using either external or internal calculation methods (de Wit 1995), (Macdonald & Strachan 2001), (de Wit & Augenbroe, 2002), (Macdonald, 2002). Similarly, this paper does not address uncertainty in modeling outcomes. Rather, this paper addresses the choice of *strategy* related to energy efficiency, and generally assumes various recognized shortcomings in energy modeling simulation tools and analyses are surmountable. The goal is to assess the *value of information* available from a given analysis *strategy* relative to an energy efficiency *challenge*. Using a crude cost-benefit analysis, we describe a method to assist in the selection of a design *strategy* as a value-add analysis technique in high performance, specifically energy efficient design. Future research may extend such findings to the broader field of sustainable design or development as tools and comparative analyses involving more subjective metrics are developed.

To perform this research, we adopt and apply a previously developed Design Exploration Assessment Methodology (DEAM) (Clevenger & Haymaker, 2010). We select DEAM for this research because, unlike other better known multi-criteria decision analysis techniques, DEAM articulates differences among *challenges* in addition to assessing or analyzing the dimensions of *strategy* and *exploration*. Here, we use DEAM to identify and illuminate variations among climate-dependent performance-based *challenges* and the differences in resulting empirical design *explorations* afforded by different *strategies*. We extend DEAM to include a method for estimating *process cost* and assess the *value* of the *guidance* provided by a select *strategy* for a given *challenge*. We describe six conceptual design *strategies*, and assess their application by designers across two theoretical *challenges* to provide a preliminary ranking of analysis *strategies* with respect to the value of information provided. We use these findings to provide insight into the strengths and weaknesses of various *strategies* in high performance building design and hypothesize about relationships between *strategy* and *challenge* in energy efficient design. We discuss the potential and limitations for this method to enable *strategy* selection or development. We conclude by proposing opportunities for additional research.

Strategies

Design *strategies* range from informal to exhaustive. Kleijnen suggests five main categories of strategies exist in engineering analysis: validation, screening, sensitivity analysis, uncertainty analysis, and optimization (Kleijnen, 1997). Ross introduces trade-off analysis as an emerging *strategy*, useful for assessing high performance building (Ross and Hastings, 2005). For purposes of this research we adopt and narrowly define four approaches for engineering analyses as outlined by Kleijnen and relevant to energy efficient design as the domain of the study. In addition, we include random guessing and full analysis to serve as theoretical limits representing a full range of *strategies* relevant to high performance design today. Next we discuss the definition of these *strategies* as used in this conceptual study.

Validation, as used by Kleinjnen consists of statistical tests demonstrating a model's ability to represent the real-world. While this typically is the first concern for most modelers, as previously mentioned, this study does not validate the fidelity of energy modeling. We consider point-analysis used for performance verification as the most basic energy modeling approach. This approach is consistent with Simon's description of the search for "satisficing" solutions, as looking for those solutions that are "good enough," but not necessarily optimum (Simon, 1987B). As we define it, verification analysis provides point predictions with little to no information regarding the predicted *impact*(s) of unanalyzed *alternatives*. Research shows that energy models used in Architecture, Engineering, and Construction (AEC) practice today are primarily used for verification. Specifically, they provide point analysis of estimated whole building performance to 'validate' that a particular design satisfies energy efficiency goals after it is mostly designed, but prior to it being built (Flager & Haymaker, 2007), (Gane & Haymaker, 2010). In such implementation, energy modelers make assumptions about hundreds of inputs resulting in the possibility of an exponentially high number of design *alternatives* (Clarke, 2001). However, modelers typically only generate and disseminate the estimated performance on a handful of design *alternatives*. Professionals using building performance modeling in such a fashion generally report low satisfaction with the tools and process. When polled, modelers and designers identify development of expanded pre- and post-processing as top priority for energy modeling (Crawley, et al. 1997).

Screening analysis performs numerical experiments to identify the few important factors that influence performance. Typically, in a model with a large number of parameters, a few inputs dominate performance (Kleijnen 1997). Researchers in other fields (Sacks et al, 1989) successfully divide input variables into control factors and noise factors. Extensive research exists to develop algorithms that successfully perform group screenings (e.g.; "one-factor-at-a-time" (Morris 1991), two-level screening (Morris 1987), (Rahni & Ramdani, 1997), and sequential bifurcation (Bettonvil, 1990), (Kleijnen, 1997). Several studies have attempted to apply such screening techniques to building energy modeling (O'neill & Crawley, 1991), (de Wit, 1995), (Rahni & Ramdani, 1995), (Brown & Tapia, 2000). Despite such efforts, many building professionals today have limited tacit knowledge of dominant factors that influence energy performance (Clevenger & Haymaker, 2010a).

Sensitivity analysis consists of the systematic investigation of how a model's outputs vary relative to model inputs. It is used to bracket individual *variables'* contribution to performance. Sensitivity analysis builds upon screening analysis, and is typically calculated either locally, varying one input at a time (high-low) holding all others constant; or globally, assessing output variability for a single input across the variation of all other inputs. Some sensitivity analyses analyze a model's responses to extreme inputs, while others may gauge the impact of more probable inputs (Kleijnen, 1997). Researchers have applied sensitivity analysis to building performance simulation (Lomas & Eppel 1992), (Furbringer & Roulet, 1995), (Lam & Hui, 1996), (Rahni et al, 1997), (Breesch & Janssens, 2004), (Clevenger & Haymaker, 2006), (Harputlugil et al, 2007), (Mara & Tarantola, 2008). Due to the inherent complexity of building simulation, most examinations have been limited to one-factor-at-a-time and have excluded geometric decisions (Harputlugil et al., 2007).

Uncertainty analysis consists of testing probabilistic distributions to demonstrate potential consequences of uncertainties or risks. To assess uncertainty or risk, inputs are typically modeled as probability distributions. Uncertainty analysis focuses on gauging the range of possible outputs to evaluate risk potential. While it assesses relationships between outputs and inputs, it is possible that a model is very sensitive to a specific input, but that that parameter is well known (certain) and plays only a very limited role in uncertainty analysis (Macdonald 2002). While several researchers have examined the role of uncertainty in energy modeling using either external or internal calculation methods (de Wit 1995), (Macdonald & Strachan 2001), (de Wit & Augenbroe, 2002), (Macdonald, 2002), this research does not currently address uncertainty.

Optimization uses mathematical calculations to identify a single or set of top performers (Kleijnen 1997), (Al-Homoud, 2001). Numerous mathematical algorithms exist or are under development to support optimization analysis across numerous engineering disciplines. In building design, a single or set of *alternatives* on Pareto frontiers may be considered optimal if no other *alternative* exists that is superior across all *objectives*. A number of researchers continue to work to apply optimization to multi-objective building design for building performance (Coley and Schukat 2002), (Wright et al., 2002), (Wetter, 2004), (Ross & Hastings, 2005), (Caldas, 2006), (Christenson, Anderson et al. 2006), (Ellis, Griffith et al. 2006), (Flager et al, 2009).

Finally, trade-off analysis is an additional and emerging *strategy* in building performance (Ross and Hastings 2005). Related, but distinct from sensitivity analysis, trade-off analysis identifies which *variables* have competing *impacts* relative to *value*. Researchers are currently exploring local points, frontier sub-sets, frontier sets, and full trade-space for such trade-off analysis.

While not an exhaustive list, we use these narrowly defined *strategies* as the basis and motivation for the four *strategies* tested (i.e.; tacit knowledge, validation, trend analysis, trend analysis plus validation) in addition to the theoretical limits we assume (i.e.; random guessing, full analysis) for energy efficient building design. We group sensitivity analysis and trade-off analysis together under trend analysis since both are capable of identifying performance patterns. In our pilot case, trend analysis is generated using full analysis. In the future, however, it will be possible to compute trend data based on statistically representative sample sizes, which will lessen the computing requirements significantly.

Cost of Strategies
In the past, researchers choosing between various decision-making *strategies* have generally assumed that processing resources are consumed in proportion to the amount of information transmitted (Galbraith, 1974). Based on this assumption, the biggest obstacle to high performance or energy efficient design is the limit of time and resources. Without these limits, the best *strategy* would always be to solve a fully constrained modeling *challenge* using full analysis followed by a deterministic selection of the highest performer. The broad concept of sustainability and computer-aided, automated analysis, however, challenge this assumption in several ways. For example, sustainable architecture as connected to larger political, economic and ethical concerns is difficult to model or definitively define (Williamson et al,

2003). Secondly, powerful computing capabilities of today tend to change the balance of resources needed to perform analyses. In traditional production, process costs are averaged over units produced during a period of time. Process costs include direct costs of production and indirect costs including equipment, set-up time, and rework. In the case where units of production are simulations analyzing *alternatives* and iteration time is in milliseconds, production costs may be insignificant relative to set-up or equipment costs. In other words, once a computer model has been built and equipment purchased, the cost of running an additional simulation (producing more information) may be negligible. As a result, the selection of *strategy* to assist in high performance design, in particular, and sustainable design, in general, is non-trivial, and the solution is not necessarily to fully analyze the design *challenge* in every instance. This research focuses on an empirical experiment performed in a simplified scenario of energy efficient design to explore whether the new evaluation method, DEAM, can meaningfully inform a selection process of design *strategy* based on the design *challenge*.

To assess the *process costs* of applying the representative design *strategies* assigned above to a representative energy efficiency design *challenge*, the authors used professional estimates of the labor necessary to set-up and run a model for each strategy. Estimates are based on the number of *objectives* addressed and the analysis iterations required by a given *strategy*. For these *process cost* estimates, we assume a labor rate of US$100/hr. Energy trend and optimization tools are currently available and under further development (examples include Ellis and Griffin, 2006, Ross and Hastings, 2005). A prototype tool (Welle and Haymaker, 2011) was used to simulate these *strategies* in this research. However, additional development cost of experimental software is not included in the *process cost* estimate. In addition, differences in equipment requirements (i.e.; processing speed etc.) are also not accounted for.

Table 1: *Process cost* estimates for *strategies*. Costs are based on estimates of the labor hours required to implement individual *strategies* assuming a $100/hr labor rate. Costs do not include labor estimates to develop a *strategy* nor associated equipment costs.

	Random Guessing	**Tacit Knowledge**	**Validation**	**Trend Analysis**	**Trend Analysis + Validation**	**Full Analysis**
Process Cost	$ -	$ 100	$ 8,000	$16,000	$ 16,100	$ 40,000

Sample Challenge

Our example high-performance building *challenge* is based on a relatively simple real-world case study - a 3 story, 100,000 sf, rectilinear office building. Table 2 shows the nine *variables* we modeled, which represent common design decisions impacting energy performance in new building construction. By using such a simple example, we limit our *design space* and provide a manageable data set, where we are able to perform all six illustrative *strategies* and systematically compare the nature of the *challenge* embodied. Table 2 lists the *options* considered for each *variable*. While we acknowledge our simplified model is not representative of the full range of challenges facing sustainable design today, by closely examining a range of available analyses in a simple case of energy efficient design, we hope to demonstrate that the DEAM method can inform the selection of design *strategies* for complex and multi-variable in sustainable design in the future.

Table 2: *Variables* and their *options* in a rectilinear office building new construction project.

Variable	**Options**	
Window Type	double-pane	double-pane, Low-E
Insulation	1.94 RSI [R-11]	3.35 RSI [R-19]
Lighting Efficiency	10.76 W/m2 [1W/sf]	8.61W/m2 [0.8W/sf]
Exterior Shading	No exterior shading	50% exterior shading
Daylighting Controls	No	Yes
Building Shape	Square [1:1 aspect ratio]	Rectangular [1:2 aspect ratio]
Building Orientation	0, +/-45, +/-90 (rotation from N)	

Window to Wall Ratio	40%	90%
HVAC System Type	Variable-Air-Volume (VAV)	High Efficiency VAV

After identifying such a simple example, we performed a computer experiment on the *challenge* modeled to better understand the nature of the *challenge* presented (Sacks, et al., 1989). Specifically we asked if the *challenge* embodied in the design of a simple rectilinear office building might change if the building were being designed in different climate zones. To perform this experiment, we used a prototype software capable of queuing model iterations of all possible combinations of *variables* and analyzing the full range of outputs (Welle and Haymaker, 2011). We then evaluated the *challenges* by using metrics previously defined and referenced at the beginning of this paper (Clevenger and Haymaker, 2011). Specifically, we used these metrics to help quantify the comprehensiveness of the *objectives* analyzed, the number of *variables* that depend upon one another, the number of *variables* where change is good according to one goal but problematic for another, and the level of dominance among *variables*. We theorize if the fundamental relationships among variables vary non-trivially in simple design *challenges* across climate zones, they certainly vary non-trivially across more complex design *challenges*.

For this computer experiment we characterize building performance (life-cycle savings above the baseline building) using net present value (NPV) according to Equation 1:

Equation 1:
NPV = Baseline Budget - First Cost($) - 30 year Discounted Annual Energy Cost($)
($.10/kWh energy cost and 3% inflation rate assumed)

We varied the climate according to the climate characterization by location used in the Advanced Energy Design Guide for Small to Medium Office Buildings (ASHRAE, 2011). Our computer experiment analyzes these metrics for one design, but locates the project in six distinct climate classifications. Table 3 lists interactive *variables*, *variables* with competing *impacts* as well as the three most dominant *variables* across climate zones. *Variables* with competing *impacts* make it difficult to maximize NPV. For example, low energy costs frequently come at the expense of higher first costs. Highly dominant *variables* indicate that those *variables* are highly correlated with maximizing NPV for the project. Table 4 shows the *challenge* metrics evaluated. In general, low *objective space size* (OSS), *alternative space interdependence* (ASI) and *impact space complexity* (ISC) values, and high *value space dominance* (VSD) value are associated with simple *challenges*. Conversely, high *objective space size* (OSS), *alternative space interdependence* (ASI) and *impact space complexity* (ISC) values, and low *value space dominance* (VSD) value are associated with complicated *challenges*.

Table 3: Computer experiment results showing the nature of and level of dominance for select *variable*s in energy efficient decisions tested using rectilinear office building design across climate types.

Zone	Climate Type	Representative City	Number of Interactive Variables	Variables with competing Impacts (tradeoffs)	Dominant Variables
2A	Hot-Humid	Houston, TX	8	1. Window Type 2. Building Length 3. Orientation	1. HVAC efficiency (29%) 2. Window Area (26%) 3. Shade Control (12%)
2B	Hot-Dry	Phoenix, AZ	8	1. Window Type 2. Orientation 3. Building Length	1. HVAC efficiency (28%) 2. Window Area (26%) 3. Shade Control (12%)
4A	Mild-Humid	Baltimore, MD	9	1. Window Type 2. Orientation 3. Daylighting	1. Window Area (28%) 2. HVAC efficiency (26%) 3. Building Length (13%)
4B	Mild-Dry	Albuquerque, NM	10	1. HVAC Efficiency 2. Building Length 3. Window Type Lighting Load	1. Window Area (30%) 2. HVAC efficiency (20%) 3. Building Length (14%)
6A	Cold-Humid	Burlington, VT	8	1. Window Type 2. Wall Insulation 3. Lighting Load 4. Daylighting	1. Window Area (35%) 2. Building Length (16%) 3. Shade Control (15%)
6B	Cold-Dry	Helena, MT	9	1. Window Type 2. Daylighting	1. Window Area (33%) 2. Building Length (18%) 3. Shade Control (13%)

To compare and contrast the nature of the *challenge* designers face when trying to design a similar energy efficient office building in different climate zones, we applied the *challenge* metrics. While the precise implications of these differences have not been fully calibrated, they begin to reveal changes in relational characteristics such as differences in:

- The level of dominance of one *variable* has over others
- The number of competing *variables* (ones with off-setting impacts)
- The level of interdependence of *variables*.

Results of the evaluation of such metrics are presented in Table 4.

Table 4: *Challenge* metrics evaluated for rectilinear office building characterizing *challenges* across climate types.

Zone	Climate Type	Representative City	Objective Space Size (OSS)	Alternative Space Interdependence (ASI)	Impact Space Complexity (ISC)	Value Space Dominance (VSD)
2A	Hot-Humid	Houston, TX	2	.44	.33	.196
2B	Hot-Dry	Phoenix, AZ	2	.44	.33	.180
4A	Mild- Humid	Baltimore, MD	2	.5	.33	.164
4B	Mild-Dry	Albuquerque, NM	2	.55	.44	.158
6A	Cold-Humid	Burlington, VT	2	.44	.44	.136
6B	Cold-Dry	Helena, MT	2	.5	.22	.140

Results from this computer experiment suggest non-trivial differences exist in the nature of the *challenge* addressed when designing the same rectilinear office building to be energy efficient in different climates. Beyond favoring different *options* for *variables*, Table 4 shows that characterization of a *challenge* is distinct per climate zone, and that each metric varies independently. If this is the case, the basis for individual design decisions and the selection of design *strategy* for making these decisions, may differ according to climate. Such findings are consistent with observations that high performance design modeling in general, and energy analysis in particular has struggled to reliably provide satisfactory results in practice. This is consistent with previous research indicating that that tacit knowledge also has limited power and transferability between building projects. Specifically, we draw the following illustrative conclusions about the *challenges* faced across climate types based on the results of the simple computer experiment performed. These conclusions are not intended to be universal, but rather illustrative of the way such an assessment might be used.

1. *Objectives* remain the same across climate types tested.
   - Supportive reasoning: Objective Space Size (OSS) remains fixed.

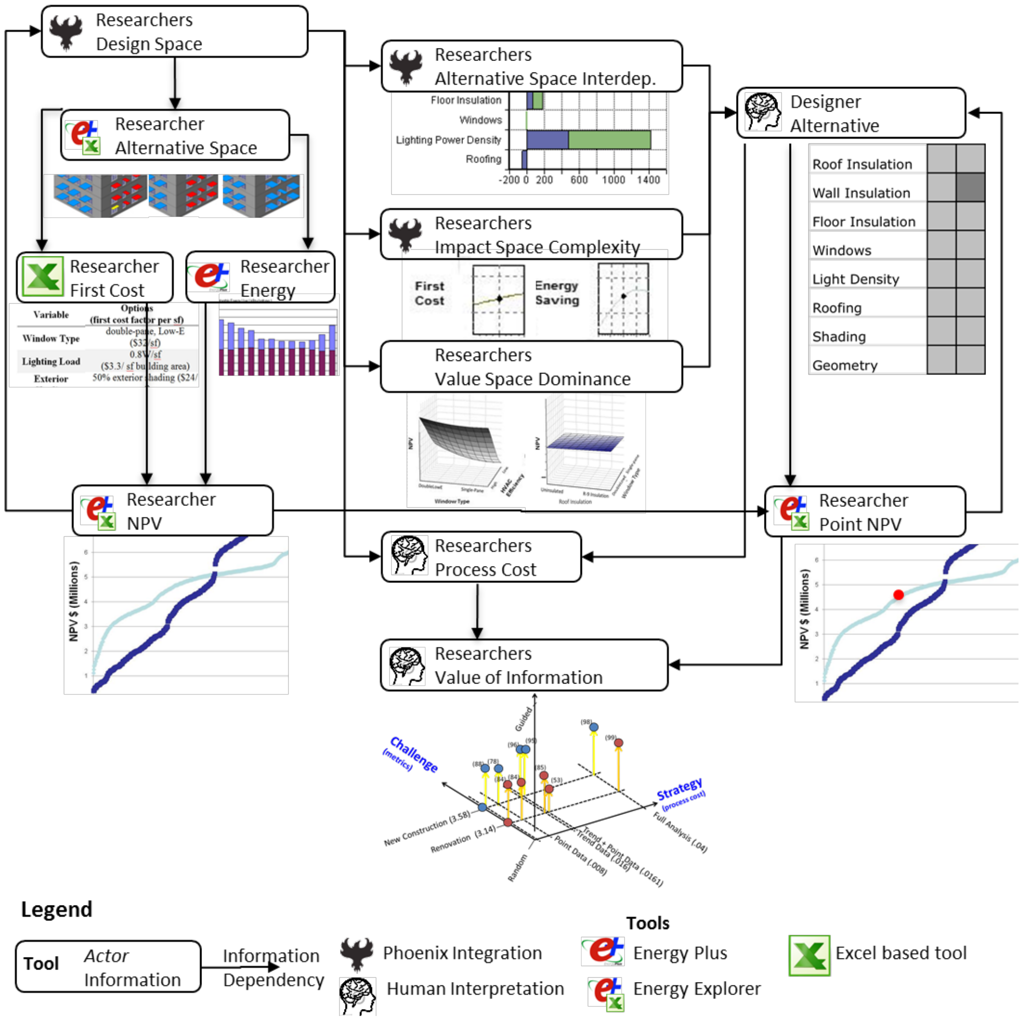
2. Dry climates tend to have more interactions among *variables* than humid ones.
   - Supportive reasoning: In general, the *alternative space interdependence* (ASI) increases for a given climate zone as the characterization changes from humid to dry. This finding merits more research since intuitively energy performance impacted by humidity as well as temperature suggests more interactive effects among *variables*. For a designer such a finding might discourage sub-optimization of *options* in dry climates.

3. The number of trades-off for *impacts* differs across climate type.
   - Supportive reasoning: Changes in *impact space complexity* (ISC) indicate anywhere from 2 of 9 to 4 of 9 design decisions might have competing impacts for the same building, dependent on the climate type. For a designer this means the number of decisions requiring a balancing act will differ, but may be unpredictable based on climate.

4. Hot climates are more dominated by (one or two) *variables* (in this case, HVAC efficiency) than colder climates.
   - Supportive reasoning: In general, the *value space dominance* (VSD) decreases across the climate types ranging from hot to cold. When designing in hotter climates, the relevance may be that a good HVAC engineer is essential to good building performance.

These illustrative findings from our simple computer experiment suggest that design *challenges* fundamentally differ across climate and motivate further investigation regarding the effectiveness of various *strategies* to promote energy efficient design across a range of *challenges*. In particular, if high performance design *challenges* fundamentally differ for simple buildings, the selection of appropriate *strategy* is, most likely, non-trivial. We investigate further to see if we can detect if and how different *challenges* warrant different design *strategies* in high performance design. Specifically we look to see if our metrics inform how to select which *strategy* will be more effective in high performance design for a given *challenge*. To do so, we calculate the *value of information* generated by six *strategies* relative to two distinct *challenges*. Figure 1 illustrates the information flow required to calculate the *value* of applying a given *strategy* to a given *challenge*. This process map illustrates how researchers first generate entire design spaces for a *challenge* (upper left) to assess its ASI, ISC, and VSD (center); researchers then run controlled experiments to measure designers' *exploration* as they use various *strategies* (right); the final step provides feedback and allows researchers and designers to calculate the *value of information* afforded by *strategies* for *challenges* (bottom center).

Figure 1: Process map showing the information flow required to evaluate the *value of information* generated from applying a *strategy* to a *challenge*.



Note, we demonstrate our method in the context of energy-efficiency, but it could apply to other multidisciplinary sustainable design problems where performance data is available.

Value of information provided by strategy for challenge

The source data for evaluation comes from two charrette tests conducted in 2009 using 15 building industry professional participants. In preparation for the charrette, the authors modeled *variables* and *options* impacting energy efficiency for a simple office building similar to the one presented in Table 2. We modeled two scenarios: new construction and renovation each with eight *variables*; the primary distinction between the two scenarios was that the renovation case fixed the geometry (building shape and window to wall ratio), and varied insulation levels in the walls and roof whereas the new construction case allowed changes to building geometry and did not vary insulation levels. We used our prototype software to generate simple cost estimates for all design *alternatives* for the *variables* and *options* modeled for both of the two scenarios. The goal was not to provide accurate cost estimates, rather, we attempted to include reasonable cost assumptions to provide internally consist data sufficient to support relative comparisons between design *alternatives* and across *challenges*. Table 5 characterizes both *challenges* using the *challenge* metrics.

Table 5: *Challenge* metrics evaluated for a renovation or new construction of a rectilinear office building. Results support characterization and comparison of the two *challenges*.

Challenge	Objective Space Size (OSS)	Alternative Space Interdependence (ASI)	Impact Space Complexity (ISC)	Value Space Dominance (VSD)	Total
Renovation	2	.58	.25	.31	3.14
New Construction	2	.70	.25	.63	3.58

During the charrettes, we used a synthetic experiment with custom-built software EnergyExplorer™ to record the *explorations* executed by professionals for two *challenges*. Charrette participants individually used four of the narrowly defined *strategies* previous discussed to support their *explorations*. The maximum *values*, VSM, achieved using these *explorations* are listed in Table 6. In addition, results from implementation generated by computer analysis for random guessing and full analysis *strategies* are also shown. In all cases, *value* is calculated using Equation 1. *Process costs* are assumed to be those estimated in Table 1. We assess the *value of information* (VoI) for each of these six *strategies* using Equation 2 which calculates the relative *guidance* afforded by a *strategy* as measured by the delta maximum *value* generated minus the cost of that *strategy* implemented.

Equation 2:

VoI= Maximum Value Generated (VSM) from Exploration supported by $Strategy_X$, *– VSM from Exploration supported by* $Strategy_{RandomGuessing}$*– Process Cost* $(PC)_{StrategyX}$

Equation 2 essentially states that the *value of information* generated is the increase in design *value* achieved over random guessing minus the cost to achieve it. Table 6 summarizes the *value of information* calculated per *strategy* based on the actual charrette data collected. Findings based on this data are summarized below. The normalized *value of information* is also provided for each *strategy*. The normalized *value of information* relates the *value of information* achieved to its highest potential value, $TV_{full\ analysis} - TV_{random\ guessing}$.

Table 6: *Value of information* assessed for six *strategies* across two *challenges*.

	Challenge	Random Guessing	Tacit Knowledge	Validation	Trend Analysis	Trend Analysis + Validation	Full Analysis
Top Value (TV)	**Renovation**	$2.622	$4.968	$4.981	$4.993	$4.120	$5.411
(in Millions)	**New Construction**	$4.829	$6.302	$6.141	$6.450	$6.430	$6.500
VoI ($)	**Renovation**	$ -	$2.35	$2.35	$2.36	$1.48	$2.75
(in Millions)	**New Construction**	$ -	$1.47	$1.30	$1.61	$1.58	$1.63
VoI ($)	**Renovation**	0	0.84	0.84	0.85	0.53	0.99
normalized)	**New Construction**	0	0.88	0.78	0.96	0.95	0.98

Using this information gathered during the charrette, we can compare the *value of the information* generated across two *challenges* and six *strategies* based on the modeled performance of the *alternatives* generated. We graphically show this comparison in Figure 2 and discuss illustrative conclusions below.

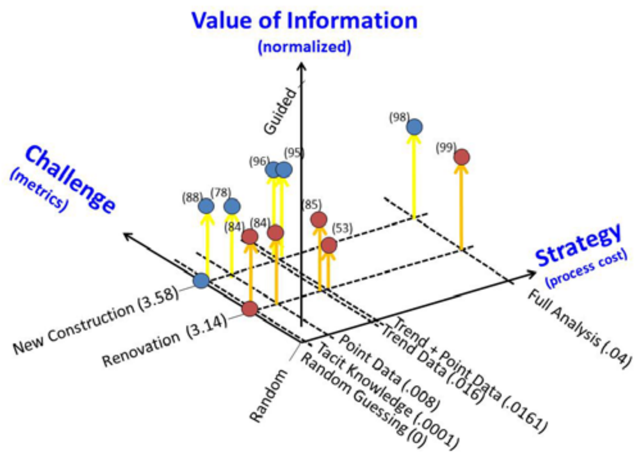


Figure 2: Diagram comparing normalized *value of information* assessed for six *strategies* across two *challenges*. *Strategies* applied the less complicated renovation *challenge* are shown in red. *Strategies* applied the more complicated new construction *challenge* are shown in blue.

These illustrative *value of information* results, summarized in Table 6 and diagramed in Figure 2, include empirical evidence to support several insights relating *strategy* to *challenge*:

1. The more complicated a *challenge*, the more *value* provided by an advanced *strategy*.
    - Supportive reasoning: In our example, the new construction *challenge* is more complicated based on a higher *alternative space interdependence* (ASI) and lower *value space dominance* (VSD) (Table 5). The normalized *value of information* is relatively higher across *strategies* for the new construction *challenge*, than the renovation *challenge*.

2. Validation provides little or negative *value*.
    - Supportive reasoning: Data shows that generating point data for validation has little to negative impact on the *value of information* provided. Specifically, the *value of information* of tacit knowledge and the *value of information* of trend analysis, two *strategies* providing no *impact* data, are higher than similar *strategies* providing point data. Possible reason for this include: data consisting of such a limited sample size even in *challenges* of this scale (totaling 574 or 864 *alternatives*) is misleading. Alternatively, providing such additional data may simply overload rather than aid the decision-maker (Galbraith, 1974).

3. Trend analysis provides positive *value*.
    - Supportive reasoning: For both *challenges*, the second most valuable *strategy* to full analysis performed was trend data consisting of sensitivity and trade-off analyses. This is an important finding, since in many cases full analysis may not be a viable option.

4. The *value* of advanced *strategies* dwarf their *process cost.*
    - Supportive reasoning: Even for our relatively small rectilinear office building example, preliminary data shows that relatively inexpensive analysis *strategies* can bring potentially significant changes to a project's expected *value*.

Such results suggest that advanced *strategies* add *value*, particularly as *challenges* become more complicated in energy efficient design.

Conclusion

In this paper, we identify representative *strategies* currently implemented in energy efficient building design. We assign these *strategies* process costs. We motivate assessment of the exploration of these *strategies* by demonstrating that even for a relatively simple rectilinear office building project, the embodied *challenge* can vary non-trivially. Specifically, we demonstrate that siting the building in a different climate zone fundamentally changes the relationships among *variables*. We then test the relationship of *strategy* to distinct *challenges* using the measure of the *value of information*. In particular, we analyze the *value of information* provided by six *strategies* as narrowly defined, illustrative decision-making processes. We collect empirical data from the application of each *strategy* to both *challenges*. Such data are critical because, in the real world, design teams rarely have the luxury of implementing several *strategies* on the same *challenge* to compare effectiveness. This work highlights the importance of having a method capable of comparing the effectiveness of a *strategy* across diverse *challenges*.

Based on the assessment of these data, we conclude that advanced *strategies* are valuable in energy efficient design, and hypothesize that this conclusion may extend to the broader context of sustainable design in general. The effectiveness demonstrated dwarfs the cost of implementation and tends to increase in *value* the more complicated the *challenge*. Such findings generally encourage the development and implementation of advance *strategies* to support high performance building design. Split incentives may exist. Building owners reap the benefits of higher building performance, while designers generally bare the cost of the performing a more advanced *strategy* for a given *challenge*. Presumably, however, owners will be willing to pay more for better designs, and this paper proposes a method that can support the calculation of how much an owner should be willing to pay. We observe the currently performed point-based verification is generally an unproductive *strategy* and, in many cases, may even be a deterrent to realizing high performance. The authors acknowledge, as have other researchers, that *value of information* calculations can result in overestimations because designers can choose not to act on the information provided, rendering the *value of information* void. In fact, in the real-world case study, which served as the basis for the example *challenge* tested (Table 2), some designers chose to do exactly that. Initial energy modeling results identified a leading, high performing *alternative*. Nevertheless, the designers chose a different *alternative* based on unanalyzed aesthetic considerations. In the vast *design spaces* of high performance building design, it is understandable and foreseeable that many decisions will involve unanalyzed *variables* regardless of the level of advancement of the *strategy* implemented. Perhaps the most encouraging outcome of this research is the finding that suggests relatively high *value of information* results from trend-analysis *strategies*, consisting of sensitivity or trade-off analysis. Trend analysis may guide designers towards high performing design, particularly in large *design spaces*, even if it does not identify specific *variable* values for the optimum design.

Future research will focus on allowing designers to more precisely align *strategy* effectiveness with the individual *challenge* metrics. Additional computer experiments can test a wider range of *variables* such as occupancy, equipment schedule, or even uncertainty. The method proposed in this paper may support the selection of a custom *strategy(s)* for energy efficient building *challenges* with specific *variables*. It provides a method for definitive valuations of how much a designer or owner should be willing to pay for the information generated by a specific *strategy* as it relates to the specific energy efficiency example. Fundamentally, sustainable design faces similar challenges to many multi-disciplinary optimization problems, with the added obstacle of including numerous unquantifiable metrics. As evaluation techniques come on-line to help quantify sustainability metrics, DEAM could be applied to these more robust design *challenges*. Or, if such metrics remain unquantifiable, it may be possible to apply DEAM to these *challenges* to assess the impact of having unquantifiable metrics, and ultimately to identify which *strategy* might be best for addressing such *challenges*.

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