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
Components
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.

Dimensions
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) alternatives for a given challenge.
- **Impact space**: analyzed impacts of alternatives 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).

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 Kleijnjen 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 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), (Harpurtlugil 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 (Harpurtlugil 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.

<table>
<thead>
<tr>
<th>Process Cost</th>
<th>Random Guessing</th>
<th>Tacit Knowledge</th>
<th>Validation</th>
<th>Trend Analysis</th>
<th>Trend Analysis + Validation</th>
<th>Full Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>$ -</td>
<td>$ 100</td>
<td>$ 8,000</td>
<td>$16,000</td>
<td>$16,100</td>
<td>$ 40,000</td>
<td></td>
</tr>
</tbody>
</table>

**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.
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:  
\[
NPV = \text{Baseline Budget} - \text{First Cost}($) - 30 \text{ year Discounted Annual Energy Cost}($) \\
(\$0.10/\text{kWh energy cost and 3\% inflation rate assumed}) 
\]

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 variables in energy efficient decisions tested using rectilinear office building design across climate types.

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

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.

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

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 trade-offs 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.

<table>
<thead>
<tr>
<th>Challenge</th>
<th>Objective Space Size (OSS)</th>
<th>Alternative Space Interdependence (ASI)</th>
<th>Impact Space Complexity (ISC)</th>
<th>Value Space Dominance (VSD)</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Renovation</td>
<td>2</td>
<td>.58</td>
<td>.25</td>
<td>.31</td>
<td>3.14</td>
</tr>
<tr>
<td>New Construction</td>
<td>2</td>
<td>.70</td>
<td>.25</td>
<td>.63</td>
<td>3.58</td>
</tr>
</tbody>
</table>

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:
\[
\text{VoI} = \text{Maximum Value Generated (VSM) from Exploration supported by Strategy}_X - \text{VSM from Exploration supported by Strategy}_{\text{Random Guessing}} - \text{Process Cost (PC)}_{\text{Strategy}_X}
\]

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, \(TV_{\text{full analysis}} - TV_{\text{random guessing}}\).

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

<table>
<thead>
<tr>
<th>Top Value (TV)</th>
<th>Challenge</th>
<th>Random Guessing</th>
<th>Tacit Knowledge</th>
<th>Validation</th>
<th>Trend Analysis</th>
<th>Trend Analysis + Validation</th>
<th>Full Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>(in Millions)</td>
<td>Renovation</td>
<td>$2.622</td>
<td>$4.968</td>
<td>$4.981</td>
<td>$4.993</td>
<td>$4.120</td>
<td>$5.411</td>
</tr>
<tr>
<td>VoI ($)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(in Millions)</td>
<td>New Construction</td>
<td>$ -</td>
<td>$2.35</td>
<td>$2.35</td>
<td>$2.36</td>
<td>$1.48</td>
<td>$2.75</td>
</tr>
<tr>
<td>Vol ($)</td>
<td></td>
<td>$ -</td>
<td>$1.47</td>
<td>$1.30</td>
<td>$1.61</td>
<td>$1.58</td>
<td>$1.63</td>
</tr>
<tr>
<td>normalized</td>
<td>Renovation</td>
<td>0.84</td>
<td>0.84</td>
<td>0.85</td>
<td>0.53</td>
<td>0.99</td>
<td></td>
</tr>
<tr>
<td>New Construction</td>
<td>0.88</td>
<td>0.78</td>
<td>0.96</td>
<td>0.95</td>
<td>0.98</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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 advanced strategies to support high performance building design. Split incentives may exist. Building owners reap the benefits of higher building performance, while designers generally bear 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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