Practical energy and cost optimization methods for selecting massing, materials, and technologies

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ABSTRACT: Available energy analysis and optimization methods do not produce fast and accurate enough results to provide guidance to professional design teams making massing and technology decisions. This paper proposes two methods using the reduced-order Energy Performance Calculation (EPC) toolkit with parametric building models and optimizers in Rhinoceros, Grasshopper and MATLAB to provide rapid feedback that gives architects more confidence in their decision between alternatives on energy and cost performance. The first method helps architects to understand and optimize the performance of a set of building massing parameters through an energy demand analysis. The second method seeks to optimize for lowest life cycle cost combinations of material and technology parameters that meet or exceed operational energy efficiency targets. The methods are compared with existing prescriptive methodologies, and tested as part of a professional office building design process to demonstrate how they can quickly and accurately lead an architectural design team to improvements in energy performance and construction cost.

KEYWORDS: Optimization, Energy, Cost, Practice, Parametric

INTRODUCTION

Design objectives such as program, construction cost, environmental performance and aesthetics are key factors in an architectural design. Conceptual design decisions, about a building's orientation, massing, materials, components, and systems largely determine lifecycle performance with respect to these objectives. Currently, these decisions are made based on a limited set of tested alternatives (Ellis et al. 2008). Research shows that successful designs require an early understanding of such objectives and the ability to explore and analyze a large number of alternatives (Kelly 2006; Suh 1995). However, with multiple objectives and constraints, the design space quickly becomes unmanageable (Simon 1969). Therefore, in many cases, limited time and budget constrains the set of design options that can be tested during conceptual design. These process deficiencies can often lead to design solutions with poor initial and lifecycle performance (Clevenger et al, 2013). Figure 1 illustrates the "MacLeamy Curve" (MacLeamy, 2004), where curve 1 shows that that the ability to vary functionality and cost is high at the beginning of the design process, and gradually decreases towards the detailed design stage. An inverse relationship can be observed with curve 2, denoting the high cost of change in later stages of design. Curve 4, models the methodology that the authors are proposing, to focus on the early stages of design where there is the highest impact, and lowest additional cost incurred for changes in the design. In traditional practice, curve 3, slow communication between architect and engineer delays decisions, making it difficult and expensive to incorporate the engineer's suggestions to the design. However, to achieve high performance targets such as the 2030 Challenge (architecture2030.org), design teams are finding it important to pursue rigorous integration at the early design stage.

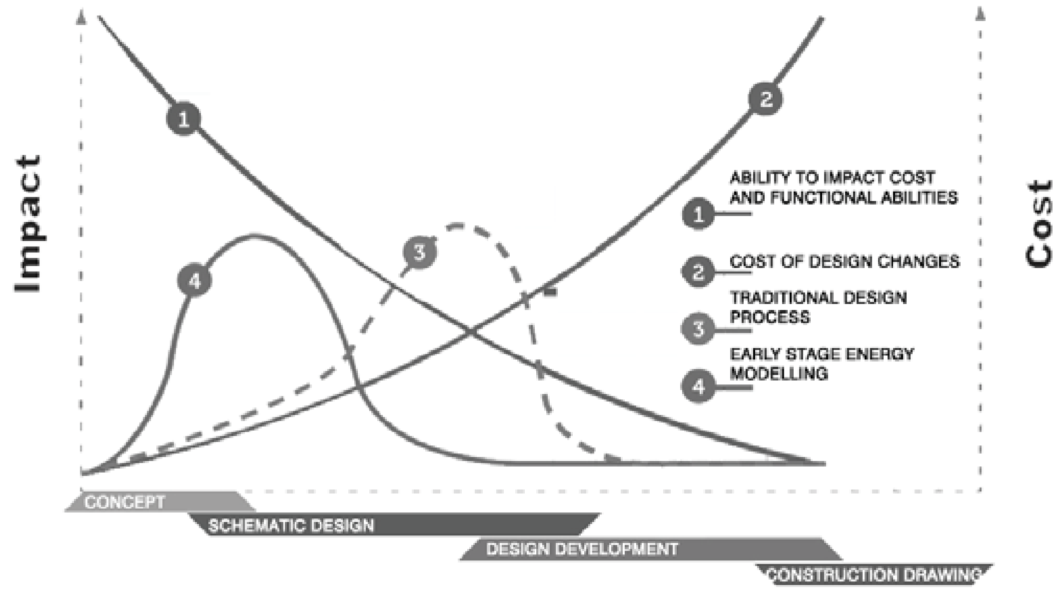

Figure 1: Macleamy's curve describes the high cost of decisions made late in the design process.

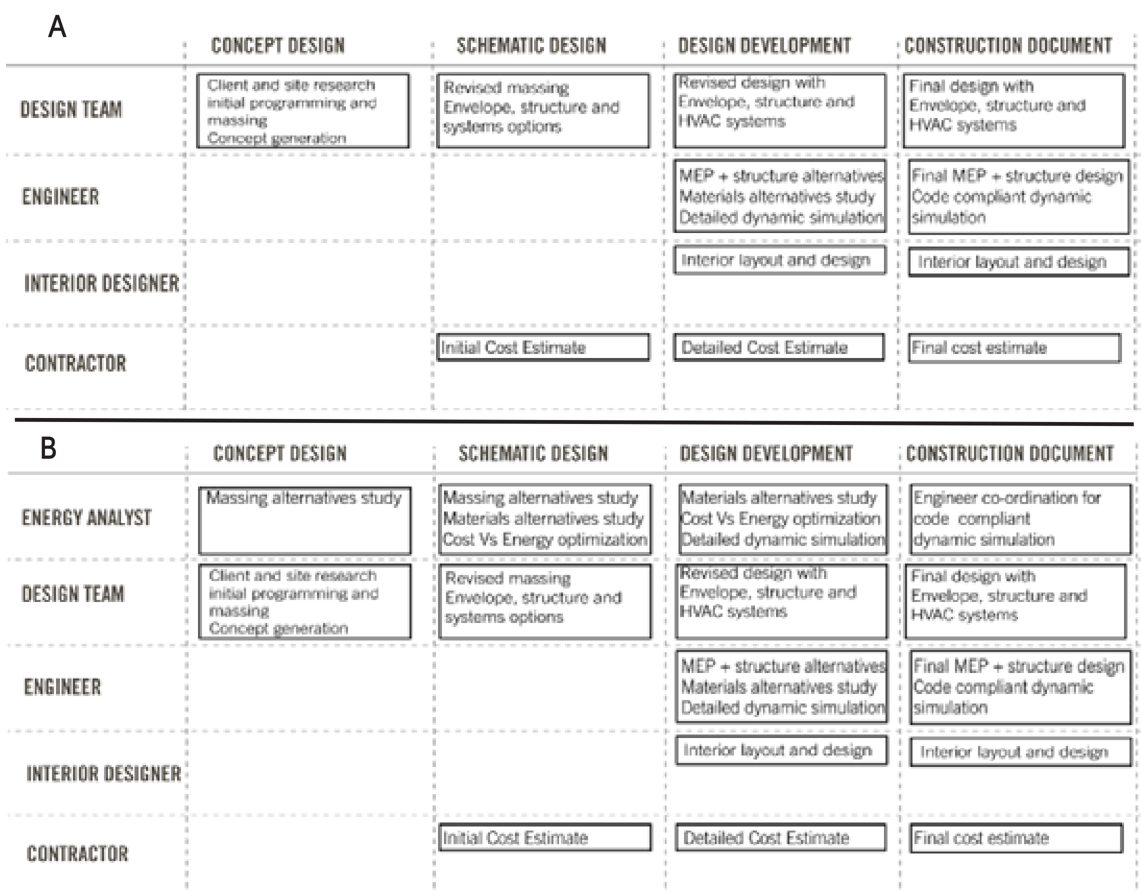

Figure 2: **A**: the authors' representation actors and processes and inter-relationships over time in 'typical' commercial building design process. **B**: Suggested variation to the current practice to achieve higher energy and cost performance.

Figure 2A depicts our observations of a somewhat typical design process for commercial buildings in the Atlanta office of our firm. During interviews with architects in our offices, we found that, consistent with recent observations (Gane & Haymaker 2010), key factors that lead to decision making in conceptual and schematic design are experience, budget, client preferences, and aesthetics with limited attention given to energy demand. To meet increasingly stringent energy codes and soaring client aspirations, designers need to integrate energy performance into their conceptual decision making processes. This requires tools that are fast and accurate enough to provide useful guidance while also keeping pace with fluid design spaces and limited budgets.

Once a design team has moved forward from the initial massing stage and after considering various alternatives and selecting a smaller list of options, they proceed to the next stage of the design where they make material and technology choices. The manufacturers of building materials, systems and technologies continue to create larger palettes of products with varying performance and cost. This variety allows for a vast array of alternatives available for buildings resulting in a very large number of technology combinations. For example, given 16 technology types, each with 3 possible options for performance and cost choice, would yield to 4.3 million unique combinations. When a contractor and architect collectively select from these options, they are unable to perceive all of choices and their impacts collectively. This leads to making inefficient selections in terms of either energy or cost or both. (Simmons et al, 2013)

Figure 2B adds a swim lane showing how parametric energy analysis can be integrated into the various steps and stages of design process. This allows feedback to the designer where it has the highest chance of being incorporated due to a low cost of design change. Dealing with the issue at the conceptual design stage, this paper offers a method to parametrically generate and test variable design options using optimization to select energy and cost efficient massing, materials, and technologies.

Our method delivers speed with accurate enough results by allowing the comparison of alternatives against each other with the confidence that we are evaluating on a level playing field. It should be noted that accuracy is not in regards to the energy consumption of the built project, but rather the relationship between alternatives is accurate (Kim, 2013). We define fast as a method that easily delivers relative rankings with low computation time along with the least possible amount of uncertainty (Kim, 2013).

We first discuss the parametric design approaches applied to enable the systematic generation of a space of design alternatives. Next, we describe analysis and optimization processes for optimizing the building massing, and then the material and system selections. We conclude by describing the application of these processes on an industry case study, and discussing how these processes can impact the efficiency and effectiveness of conceptual design processes.

1.0 PARAMETRIC DESIGN SPACE

The first step of the overall process utilizes parametric modeling to represent geometric entities with editable attributes, and associative relationships. Attributes can be expressed by independent values, which act as input to the model, or be dependent on other attributes in the model. Variations of these inputs generate different solutions of the model.

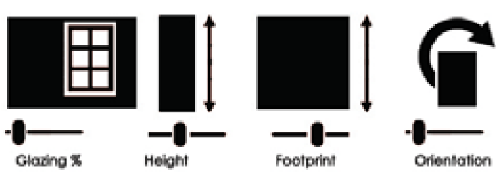

Figure 3: Common geometrical parameter for commercial office building.

Parametric models consist of variables and constraints. Variables are the primary drivers of geometric variations. We distinguish between two types of variables: *independent* and *dependent*. An independent variable is a user defined numeric input whose value can actively be controlled and changed while the dependent variable is the output whose value changes as a result. Constraints help delineate the range of variations that a parametric model can sustain. The extent of the range and the exact outcome of each geometric variation will be determined by the type of constraints used in the geometry definition process (Barrios, 2005). Figure 3 demonstrates the definition and variation of a typical parametric design space for a commercial office building.

2.0 MASS OPTIMIZATION

Reducing energy demand is a key early design consideration in architecture today. In this paper, the energy demand analysis of the building design is calculated using an energy performance calculation (EPC) toolkit developed by the Building Technology group at Georgia Institute of Technology. The EPC is a quasi-steady state model that approximates energy flows in a building at the macro level. It is based on a simplified description of a building and ignores detailed dynamic effects (Augenbroe et al, 2013). This simplified tool can quickly generate a comparison between the design options and the ASHRAE 90.1 baseline buildings. The use of this normative calculation is chosen instead of a dynamic simulation tool on two counts:

1. A set of normative modeling assumptions makes the method transparent thereby greatly reducing the potential for possible modeler's bias.
2. By using normative usage scenarios, the calculation only focuses on how the building behaves under assumed conditions (Lee et al, 2012), allowing EPC to be a strong comparative tool to study the impacts of varying geometrical parameters in the building.

The authors created a component in the Honeybee/Ladybug (Roudsari, 2015) plug-in that allows the geometry component in the EPC calculator to be directly linked in the parametric design space of Grasshopper. The definition allows the designer to set varying building parameters outputting different window to wall ratios, ceiling heights, length vs width, orientation, overhangs, internal shading, and photovoltaics panels to interpret their impact on the building energy performance. The plug-in separates the geometries by walls, surface, and roof. The walls are further segmented into opaque or glazed areas based on their properties. The surface area of each of these building geometries contribute to the heat flowing in and out of the building and hence the energy demand. These surface geometries are then separated into 8 possible directions (North, Northeast, East, Southeast, South, Southwest, West, and Northwest). These surface directions yield differences in the energy demand with the change in orientation. Since the EPC calculator requires the building geometry to be collapsed in these 8 directional categories, even the most complex design case can be simplified into an 8 sided box, greatly simplifying the modeling and analysis inputs.

Most of the geometrical inputs into the EPC are controlled by variables dependent on each other. For example, the parameter connected to the building height directly enters the EPC calculator to represent any change in building height. In simple geometries, the height parameter is also used in conjunction with the area of the floor plate to enter the volume input. The change in overhang depth is modelled by capturing the angle formed between the center of the window and the top of the overhang. The changing depth can be classified into four overhang angle ranges less than 30, 30 - 44, 45 - 59 and more than 60. See Figure 4 for illustration of the inputs for overhangs, fins, and horizon angle.

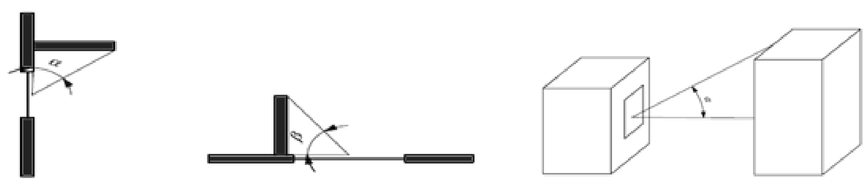

Figure 4: Showing the external shading factor calculation.

When a new design is constructed, these parameters are constrained to meet the site conditions and any other restrictions based on the client and design intent. They are then prioritized with respect to each other to determine which parameter should be the major driver of the design. Once, the priorities have been set, the various parameters are sent to "Galapagos", an optimization script (Simmons 2012) in grasshopper. It uses the energy analysis from EPC calculator to determine the combination of values yielding to the lowest energy demand. This allows us to test a wide range of building massing options and selecting a range that can be further explored to meet other design objectives. Along with the geometric option that can be varied in the grasshopper interface, other parameters that can be adjusted inside of EPC can be seen in figure 5.

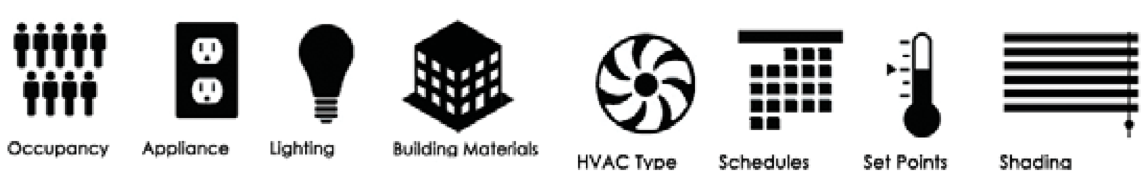

Figure 5: Author graphical representation of editable parameters in the EPC excel interface.

3.0. MASS OPTIMIZATION CASE STUDY

A practical application of the process currently under discussion is a new office building near Columbia, SC. This project is led by a progressive design principal and typifies a type of practice where small agile teams work in an iterative fashion to realize the collective design goal.

The project began with discussions with the client about their goals as an organization and understanding their current needs. This tied directly into choices about concept, site, and massing. Incorporating energy early into this process, Figure 6 demonstrates how the design team iterated over multiple massing ideas looking for the driving factors in the design. The lead two authors, acting as energy analyst on the team, provided feedback regarding the impact of various building footprints, orientation and glazing percentages (option 1-8) that the design team generated. Since energy impacts of design decisions are often counterintuitive, the design team found they could enhance the design by rotating the building by 17 degrees off the true North/South orientation to reduce the energy demand by 7%. In contrast to a detailed energy model, the team was able to test multiple glazing percentages by orientation in a single day, 8 working hours.

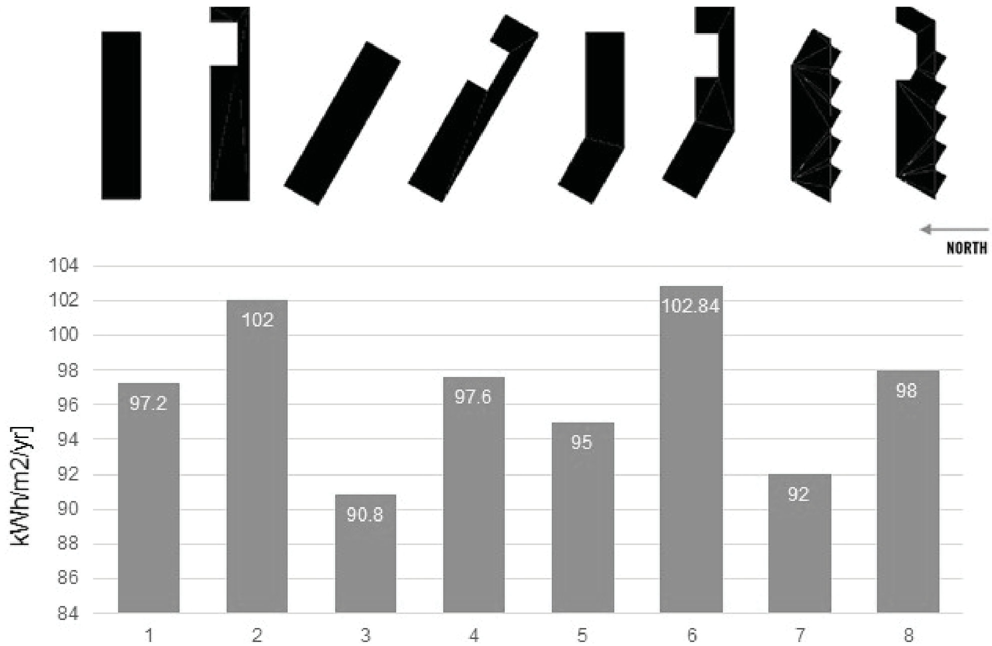

Figure 6: Representation of varying energy demand with varying massing.

The team went back to the client with the strategies generated giving them the confidence that the team possessed firsthand knowledge. This energy feedback proved vital to defining and tracking the client's energy goals for the project. As the design continued to progress, the energy model kept pace, allowing the tracking of performance across design decisions. The parametric energy analysis process and embedded energy modeling experts in the project team supported the fluid nature of the process by providing feedback on designs with fluctuating levels of detail.

4.0 MATERIAL AND TECHNOLOGY OPTIMIZATION

The material and technology optimization method, developed by the Building Technology group at Georgia Institute of Technology, searches the discrete combinatory space by maximizing the objective function: calculated energy savings divided by premium cost. The algorithm is codified into a custom MATLAB script and when compared to prescriptive methodologies is shown to be much more cost effective and can be applied given a range of building technology alternatives and their corresponding cost data (Simmons 2012).

This method also utilizes the EPC as the underlying energy engine for finding the optimal mix of technologies. The resulting EPC calculation tool is used by the optimization algorithm to evaluate the combinatorial space of technology parameters. It should be stressed that the optimization problem is only well posed at the whole building level. As a consequence, optimality can only be defined at the whole building energy outcome level (Augenbroe, 2011).

Optimization requires a metric to rank the effectiveness of each combination. Simmons et al, 2013) developed a method to rank designs for energy using a cost versus percent energy savings metric. The challenge in the past is that analysing the thousands of combinations of options for a typical building required days of calculations using EnergyPlus. By using the EPC and a custom MATLAB script developed at Georgia Tech, one can harness the computationally light EPC to run thousands of combinations in as little as an hour. Thus, we have both a metric and a methodology that can be used in the fast paced world of architecture.

In this methodology, all of the inputs in the EPC are available for optimization by considering each technology option with its performance and associated cost above a baseline case. The baseline case here is considered to be the case which meets the ASHRAE 90.1 baseline. While performance values are easy data to get from manufacturers, cost data is more difficult to find. Construction cost varies from region to region and often from city to city due to transportation and labour costs. Close coordination with the contractor is the most effective means of finding true cost data. However, RS Means or other construction cost database can also be used. Typical inputs to optimize include: Daylight controls; Occupancy sensors; Constant illumination controls; HVAC system type; Heat recovery methods; Exhaust air recirculation methods; Envelope tightness; Hot water fuel type; Building energy management systems; Photovoltaic type and amount; Lighting fixture type ; Appliance efficiency; Roof type; Wall type; Glazing type; and Solar hot water collector.

Within each category the design team can include as many options as they like. A design space of 16 parameters has 170 million possible combination. The optimization routine solves for these combinations by using a combined ascent and descent method (Simmons 2012). The algorithm increases the cost and percent energy savings until it reaches the target percentage. Once there, it backtracks minimizing cost while maintaining the percentage reduction. Close coordination between the architect, contractor, and mechanical engineer ensures that the options under consideration have accurate energy vs cost information.

5.0 MATERIAL AND TECHNOLOGY OPTIMIZATION CASE STUDY

To illustrate the use of this method, we collaborated with a senior project designer and his team to analyze a 156,000 square foot, 8-story office building in Charleston, SC as a case study. As communicated by the design team, this project near the river had employed the rule of thumb approach to come up with a design. All selections were highly typical of office building construction in the Southeast to maximize the functionality of the design. The building is a typical cast in place concrete structure with a continuous glass facade on all sides. As designed, the office building performed just slightly better than the ASHRAE 90.1 2013 baseline. Running the material and technology optimization process on this building yielded to an additional cost of \$883,065 for a 60% energy performance improvements as compared to the ASHRAE 90.1 2013. Since the overall estimate for the building was \$27 million, a 60% (4.03 Kwh/sqft) reduction in energy was achieved for 3.3% increase in the estimated cost. With the current price of electricity approximated at 9 cents/kwh, this meant a payback time of 10.4 years. The estimated payback time is likely to decrease with the rise in electricity costs in the upcoming years demonstrating the achievable impact of this process from an energy and business perspective.

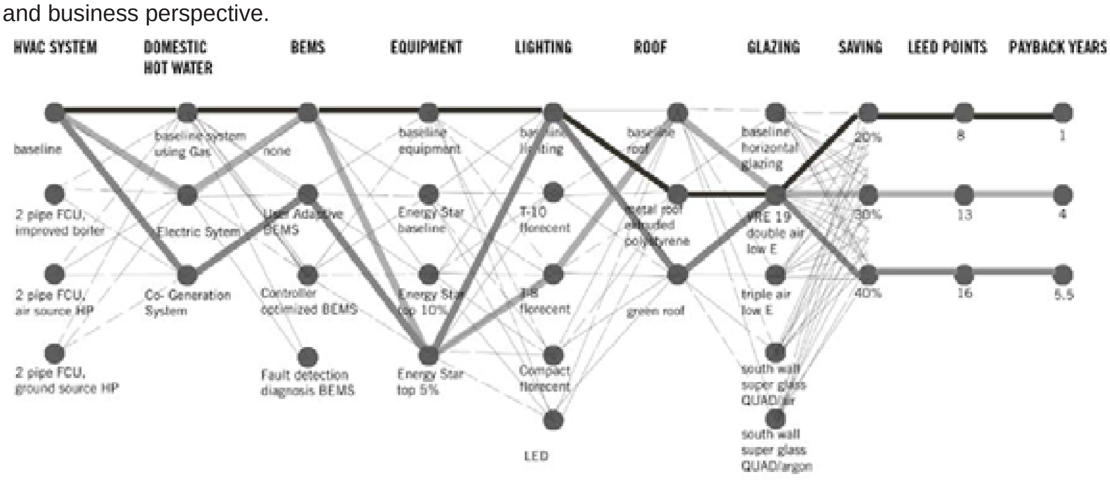

Figure 7: Possible energy savings for cost and energy optimized material and technology options. Three possible options out of the total 50,000 options are presented by the darker lines.

CONCLUSION

Emerging tools like Rhinoceros and Grasshopper are enabling integrated modules and scripting environments that are narrowing the gap between architects, engineers and computer programmers. This paper looks at emerging design tools and the current process and begins to test where parametric enabled energy analysis processes might be efficient enough to provide effective design guidance.

The rapid feedback method can use optimization to create a design space to select materials and technology options while balancing cost versus percent energy savings. Building upon this first step, the mass optimization process enabled the generation and analysis of orders of magnitude more design alternatives. Thus allowing the exploration of designs that were substantially more energy efficient than those typically evaluated using current methods at negligible additional process cost.

The material and technology optimization allowed the design team to analyze 186 more material and technology combinations than the typical 3 to 4, for a 60% energy savings and 8 years payback time at minor additional process cost. This can yield highly accurate and useful results with an accurate and diverse cost estimate. Since contractors often offer only one material and technology pricing option, the material and cost optimization is approximated using industry standard cost estimating tools like RS Means. Future suggestions include proposing the creation of an integrated contractor and mechanical engineering team to allow for more accurate inputs to increase the accuracy of the optimization process and reduce any duplication of work.

Contemporary parametric design, analysis, and optimization tools give us the possibility to enhance multidisciplinary communication and design exploration. However, to date, these methods have resided in domain specific tools and required computational and engineering design experts to formulate the models, meaning these models have taken too long and been too expensive to be effectively applied in the early stages of design. The methods in this paper match the design iteration speed of architects providing high performance building decisions to be integrated with design from the very beginning of a project.

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