NEW METHODS FOR THE CONSTRUCTION AND INTERPRETATION OF HIGH
DIMENSIONAL PARAMETRIC BUILDING ENERGY MODELS

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ABSTRACT
This paper explores a new method for providing designers with relevant, comprehensible information about potential design variation at appropriate stages in the design process. We propose leveraging both modern CAD software, which allows digital models to be controlled parametrically, and modern computational architectures, which allow access to massive amounts of computing cycles through the use of computation clusters and clouds, to quickly create, enumerate, simulate and analyze large populations of design alternatives. Analysis of these populations is accomplished through the use of both graphical and statistical treatment of the simulation output.

INTRODUCTION
The current practice of high efficiency building design usually sees a strict division of labor between design and technical personnel. Given that most simulation tools have come to reside on the engineering side of the traditional architecture/engineering design team structure, and that engineering consultants are often minimally involved in early stage design processes, Building Energy Simulation (BES) is typically conducted after a building design has been developed in detail. This is unfortunate, since the earliest stages of design development are in fact the locus of many decisions that have significant consequences for the eventual performance of the constructed building. More specifically, we have argued that a lack of access to comprehensible, information-rich, design spaces in the earliest stages of the design process leads to the over application of rule-of-thumb methodologies and a reliance on generalized design guidelines on the part of even the most well-intentioned design teams (Pratt & Bosworth 2011). Given the complexity of many contemporary design problems, this prevents design teams from discovering and exploring viable design alternatives that do not obviously follow well established normative strategies that are part of what might be called the sustainable design "playbook", such as the heliocentric section, or the use of seasonally tuned shading systems.

This paper explores one potential method for solving this problem and providing designers with relevant and comprehensible information about potential design variants at all stages of the design process. We propose leveraging both modern CAD software, which allows digital models to be controlled parametrically, and modern computational architectures, which allow access to massive amounts of computing cycles through the use of computation clusters and clouds, to quickly create, enumerate, simulate and analyze large populations of design alternatives.

The ultimate goal of this line of research is to develop tools and techniques that will allow architects to understand the effects of design decisions at a variety of scales of detail and without inherently privileging qualitative or quantitative analysis. The simultaneous and interactive display of the simulated energy use of both an individual building and of high-dimensional populations of similar buildings defined by a parameterization process provides insight into the effects of design decisions. Goals are three-fold: 1) Continued development of integrated CAD and BES tools that allow experienced but not necessarily expert users to create and simulate parameterized models. 2) Development of statistical methods of analyzing a parameterized model space to expose the level of impact of each parameter. Such an analysis provides opportunities for potentially shrinking very large parameter spaces and providing design decision insight to architects at very early stages of design. 3) Development of graphically oriented statistical tools for navigating and understanding the fully simulated design space with the intent of understanding the interactions and impacts of design decisions.

The statistical tools presented were developed from strategies typically used by scientists and engineers to design experiments. Even though we present here the application of ideas from the field of scientific experimental design to architectural design problems, some critical differences between architectural design processes and design of experiments should be pointed out. In experimental design one would like to choose...
the factors that are most likely to have the largest effect on the responses of interest. Experimenters go to great lengths to separate and control the circumstances of the experiment such that there are no factors external to the project that can have major effects on the responses. In contrast, architects must always consider factors outside the bounds of quantifiable simulation that nonetheless place important pressures on the decisions being made. Thus we present here techniques to aid in understanding the responses of buildings to quantifiable design choices, which can be computed and simulated, with the understanding that the decision context is larger than that represented by the experimental design. The intent of these tools is not to function as an expert system in the decision-theoretic sense, capable of making decisions, weighing the value and sensitivity of information (Russell & Norvig, 2003), but rather to provide a clear and understandable context in which the designer can make better holistic decisions.

GEOMETRY CREATION AND MODEL PARAMETERIZATION

For the purposes of this research we have utilized Sustain, a Java-based software suite for BES management developed at the Program of Computer Graphics at Cornell University, and Rhinoceros 3D (McNeel, 2011), a commercial NURBS modeling package frequently employed by architectural designers. The parametric modeling capabilities are provided by Grasshopper (McNeel, 2011), a visual scripting plug-in available for Rhinoceros. Grasshopper provides parametric access to the geometric modeling capabilities of Rhinoceros via a graphical interface that allows methods and functions to be "wired up" to pass variables (both geometric and non-geometric) between discreet components, which are, in fact small chunks of code that are analogous to functions or procedures in traditional programming languages.

A typical parametric design workflow in Rhinoceros and Grasshopper intended for BES includes three stages (Figure 1). First, a set of parameters is defined (Figure 1 A,B.). Second, the parameters drive the generation and modification of a building model described by curves, surfaces, and solids, represented as polygon meshes or as NURBS geometry (Figure 1 E,F). Finally, geometry and meta-data are exported to Sustain for simulation either as single buildings or batched as large parametric sets (Figure 1 C,D,G,H). We have developed a set of add-on components for Grasshopper which integrate with typical parametric modeling workflows in order to output geometry to the Sustain analysis package (Pratt et. al. 2011).

Preparing a model for a batch simulation requires specifying which parameters should be varied in the simulation, and assigning those parameters names and units. Numeric parameters in Grasshopper are frequently defined with the use of number sliders (see Figure 1 A), which provide a user interface for the selection of a single parameter value within a defined range. Connecting these sliders to additional components for generating geometry allows quick visual feedback about the effect of variation of a particular parameter. The workflow in Grasshopper requires two additional components to go in between a parameter slider and its driven geometry, but still preserves this visual feedback, providing a minimal interruption to the operation of the parametric model. The first of these components, the Batch Variable, (Figure 1 B) takes a slider as input and extracts its numeric range, current value, and name label. It also requires the definition of a unit name and a number of steps across the range to test in the simulation. The output from this component is passed to the second component (Figure 1 D), the Batch Driver, which accepts an arbitrary number of such Batch Variables. The driven geometry that was previously controlled by the slider can now be connected to an output of the batch driver, restoring its dependence on the value of Figure 1 Grasshopper definitions for the creation of simulation compliant geometry and metadata export
the slider. Variables for the batch simulation need not be defined as even steps along continuous ranges; an additional Batch Variable component will accept an arbitrary list of values to move between, along with a name and unit definition. These are used to specify non-geometric parameters like assembly definitions.

The Batch Driver component, when switched to "run" mode (Figure 1 C), outputs a complete set of Sustain files for every possible combination of the input variables through the Export Component (Figure 1 H.) The Geometry Translation Components (Figure 1 G) convert standard Rhino geometry into material and assembly definitions appropriate for simulation.

**Example Parametric Model**

Figure 2 shows a completed parametric model in the Rhinoceros environment and the corresponding Grasshopper definition that generates the building geometry and controls the parametric variation. The model enumerates potential design variants of the recently completed Milstein Hall at Cornell University, designed by the Office of Metropolitan Architecture for the university's college of Architecture, Art and Planning (Figure 3).

The model is parameterized in six dimensions, meaning that six inputs control the following variables:

1. Building volume shift between existing buildings immediately East and West of the building site.
2. Second floor slab to slab height.
3. Percentage glazed of the vertical surfaces.
4. Percentage glazed of skylights.
5. Skylight position.
6. Window glazing type (triple, double and single pane units).

When processed by the Sustain Grasshopper components the parameterized model produces 8,400 variants, which are ready to be read, simulated and analyzed. A subset of these variations can be seen in Figure 4. Obviously, the intent of this model was to study the effects of envelope configuration, material composition and siting on the potential performance of the building. To this end it was prepared for simulation by EnergyPlus V.7.0.0.23 (EERE 2011) as a two zone model with a default purchased air mechanical system. The simulation produces a single dependent variable for analysis: yearly carbon footprint in kg-CO₂/m². All simulations were controlled and managed by the Sustain software, as described in (Pratt & Bosworth 2011).

**PRE-PROCESSING FOR PARAMETER REDUCTION**

Design for Experiments is a field of research in statistics that enables one to understand large trends in a population or system with relatively few samples. Election polls, for example, are designed to expose opinions in a large population without having to ask every single individual. When every individual who cares is asked (an election) it is considerably more expensive, and no conjectural statistics are required because one has sampled the entire field. Our use of experimental design techniques to inform architectural
design decisions is unusual and condensed in that the analysis of experimental error, particularly instrument and recording errors, is not applicable to analysis of simulations.

An experiment is composed of a system that will have treatments applied and the responses recorded. The treatments are the independent variables: the variables under manipulation by the experimenter. The responses are the dependent variables: the variables not under direct control, but of interest to the experimenter. By analogy, parameterization of a building model requires a number of independent variables to be declared, each with a range and a number of discrete values as described earlier. By simulating the building model the system reacts and a result of interest (carbon equivalent footprint, energy use intensity, or site energy use, for example) is recorded as the dependant variable.

Analyses of Variance (ANOVA) are mathematical techniques used to discern how effective and significant experimental treatments are on experimental responses. They allow for better understanding of the impact of individual treatments than simple one-dimensional sensitivity analyses where a single variable is changed while keeping the rest constant. The goal of ANOVA analysis is to describe how likely it is that a group of measured samples reflect the statistical mean and variation of the full population. The use of ANOVA analysis requires that a null-hypothesis is assumed which states that measured samples with a treatment applied have the same mean and variation as samples that might have been taken without the treatment applied. In short, the null-hypothesis assumes that the treatment had no effect. Means and standard deviations of groups of measured samples are processed producing a metric called the F value. This F value is the ratio of two independent random variables each divided by its degrees of freedom (Reddy 2011). Box et. al. relate the F value to the familiar engineering metric of signal to noise ratio: the numerator of the F value is a measure of signal and noise combined while the denominator is a measure of noise alone (Box, Hunter & Hunter 2005.) Thus, the higher the F value the higher the signal to noise ratio. The calculated F value is normally compared to critical values of the F distribution at various significance levels (Figure 5). The null hypothesis is concluded as false if the F value is above a critical value defined by a significance level. For example, in Figure 5 the treatment is concluded to have an impact at a significance level of 25%, but would fail at the 5% and 1% significance levels. Details of the calculation methods associated with ANOVA analysis are beautifully treated in both (Reddy, 2011) and (Box, Hunter & Hunter, 2005).

In applying ANOVA to a parameterized model we will consider each value of each parameter as a treatment. The F value of each parameter provides a means of comparing the overall impact of each parameter on the outcome of the simulations. Sampling is done by sequentially locking the value of each step of the parameter and randomizing the remaining parameter.
values. For example, in a five dimensional parameter space, and considering the second parameter with four possible values, the sequence is \{\text{*0***}, \text{*1***}, \text{*2***}, \text{*3***}\} where * represents a random value chosen within the range of possible values of that parameter. The number of samples required to reach an F value that is satisfactorily discernable from the critical value depends on the actual strength of the effect of the parameter, the significance level chosen, and the number of steps in the parameter space. In our experiments we have found that high impact parameters can have F values an order of magnitude larger than the critical F value, even at significance levels of 1% with only around 20 samples for each parameter step. More sampling raises the calculated F value and reduces the Critical F Value. Parameters with lesser impact may require 60 or 120 samples per parameter step before they can be judged to disprove the null hypothesis with reasonable significance levels. We consider a parameter inert or ineffective if it cannot be shown to disprove the null hypothesis with a reasonable significance level after 120 samples.

This analysis divides parameters into three broad categories. We consider a parameter very active if the F value is a factor of 10 or more above the 1% critical significance level after only 20 samples. Intermediate parameters will require 60 to 120 samples per parameter step before they can be judged to disprove the null hypothesis with reasonable significance level. Inert parameters cannot disprove the null hypothesis at the 1% significance level after 120 samples at each parameter step.

In practice an energy modeler or architect is typically very careful to restrict the number and steps of the parameterization to those that are known (or assumed) to be important with the intention of restricting the number of simulations and associated cost and time. Imagine a parameterization with 10 parameters, each with 10 steps: 10^{10} possibilities, a very large design space indeed! Using an ANOVA pre-screening process 20 samples can be taken from each parameter: 10\times10\times20=2000 simulations, a quantity easily within the reach of modern computing infrastructure. Judging the relevant and high impact parameters can be done based on information instead of rule-of-thumb or best guess with very little overhead. Parameters with very high impact (high F values) should be included, parameters with low impact are left to the discretion of the myriad other forces that influence architectural design but may not be quantifiable.

**Example ANOVA analysis**

ANOVA analysis applied to the Milstein parameterization shows that the percent glazed on walls parameter is a very active parameter with F values nearly an order of magnitude greater than the critical value even at sampling levels of 20. The slab height parameter, percent glazed skylights parameter, and window material parameter are classified as intermediate parameters with unconvincing F values at the 20 sample level, but having a clear impact at 120 samples. The skylight position parameter is distinctly an inert parameter displaying F values well below critical levels even at the sampling rate of 120. The volume-shift parameter falls in a grey area between intermediate and inert classification as it just barely passes the critical threshold at 120 samples.

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<tr>
<th>Parameter</th>
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**SEARCH SPACE NAVIGATION**

Once the design space has been trimmed to include only the most relevant parameters, the fully enumerated simulation of the reduced design space is executed. Instead of automated algorithmic search, which tends to produce a narrow band of solutions, or even more unhelpful to a design team, one single optimized answer, viewing and understanding the structure and topography of the entire design space has been shown to be beneficial to architectural "wicked" problems (Pratt & Bosworth, 2011.) Methods have been demonstrated that begin to enable holistic graphical understanding of the topography of design spaces. Three graphical user interfaces are used simultaneously to display the parameterized design space (Figure 6). In the Main Console one version of the building is displayed (one single point in the design space) and detailed analysis of hourly energy use and daylighting is available. In the Voxel Plot colorized voxels (volumetric pixels) display simulation results from three dimensions of the design space simultaneously. In the Sustain Batch Controller a parallel co-ordinate plot is used to display the entire design space within a cutoff slice to allow for better understanding of clusters and trends in the data. The current model is displayed simultaneously as a highlighted voxel within the voxel plot, as a white line trace in the parallel co-ordinate plot, and in full detail in the Main Console (Pratt & Bosworth, 2011.)
Nearest Neighbor Display

Although the colorized voxel plots and the parallel coordinate plots provide clues to the location of clusters of high performing variants and the nature of global trends in parameter effects, they do not provide a great deal of insight into the topography of the design space. It is useful to know, for example, if the area of design space under investigation is generally flat, implying that changes in the parameter in that area will have relatively little effect on simulation results, or if the current building is located on a point of inflection or singularity like a ridge, peak, or saddle. These features can be easily understood graphically by displaying nearest neighbor slope vectors at every current building value of the parallel coordinate plots (Figure 7).

Nearest Neighbor slope is the difference between the current result and the result of each of the adjacent values in one parameter dimension. A peak is recognized by a situation where all of the parameters have a V shaped pair of nearest neighbor vectors all pointing in the same direction. A saddle is recognized by some nearest neighbor vectors being V shaped and pointing up, and others V shaped and pointing down. A ridge is visible when one nearest neighbor vector pair is flat while another is V shaped. Finally, relative flatness of the immediate terrain is understood by the flatness and direction of the nearest neighbor vectors.

Main Effects Display

The ANOVA analysis leads to an understanding of the impact of each of the parameters as a whole. A fine-grained analysis of the effects of individual steps in parameter space is possible through factorial experimental design, specifically statistical analysis of main effects.

In the immortal words of George Box, factorial design is there to determine "Which Factors do What to Which Responses" (Box, Hunter & Hunter 2005.) A $2^3$ factorial design is one in which three factors are considered (A, B, and C), each with two possible states (1 and 2), and it is desired to know which has the largest (or smallest) impact on the simulation outcome response. Eight experiments are required to fill in the result space, often visualized as a cube plot (Figure 8a). Each corner of the cube plot represents the result of one experiment. Each face of the cube plot represents four experiments in which one variable was held constant (Figure 8b). The main, or average, effect of one factor is calculated by averaging the differences between two parallel faces of the cube. The main effect represents the average global effect of changing that particular variable from one fixed point to another.

Implementation

There are key differences between the typical use of factorial experimental design techniques and this application to architectural design problems. First, doing one experiment (one simulation) is considered cheap. In fact, by this stage we have already simulated the entire design space. Blocking methods, meant to reduce the number of experiments needed while maintaining statistical significance, are therefore not needed. Second, the usual analysis of errors is not needed. Simulated results do not require an analysis of instrument precision and accuracy errors, or experimenter recording errors.

For use in parametric analysis we often have many more variables than three and many more levels than two. As we are interested in the effects of step changes in parameter space, the problem is divided into a series of $2^k$ hyper-cube factorial designs, where k is the number of parameters. The main effects are calculated for each step in each parameter by considering the change between the current state of the parameter and
its neighbor (Figure 9a). For each position of the sliders in the Batch Controller the impact of moving away from that position is calculated.

**Graphic Representation**

The main effects for each step in the parameter space are displayed on the parallel co-ordinate plot as vertical bars originating from each step node normalized and mapped to fit within the distance between bars (Figure 9b). The whole display allows the user to quickly assess which steps in parameter space will have the largest and smallest global effect on the outcome, and quickly guides the eye toward areas to be avoided and areas of design importance.

Parameter nodes with large positive or negative main effects reflect points and regions of significant influence from that parameter, while low main effect values reflect regions in design space where changing the value of the parameter at that location will have very little effect on the results. The combined and interactive display of main effects and nearest neighbor slopes provides a navigation tool that allows the user to understand the effects of moving through parameter space from a very local result and from an intermediate understanding of the global effects of moving locally.

**Example Analysis**

Main Effect analysis applied to the Milstein parameterization shows that there are distinct areas of the parameter space where changes have a high impact and other areas where changes are insignificant (Figure 10). The percent glazed walls and skylights parameters have high impact when moving from low percentage glazed, and the impacts of changing the parameters become less significant as the percent glazed grows larger. The placement of the skylights has small main effects.

![Figure 9 Main Effect Calculations (a) and Main Effects Display (b) on Parallel Co-Ordinate Axes](image_url_a)

![Figure 10 Nearest neighbor slope and main effects shown in batch controller interface. Note peak topology indicated by downward nearest neighbor slopes in both directions at point (A), large main effects associated with enlarging windows beyond a certain percentage (B), and relatively minimal effects of changing glazing from triple to double pane units (C).](image_url_b)
effects across the entire parameter space. The main effects display provides a higher level of detail than the ANOVA analysis. From the ANOVA analysis we knew that the percent glazed parameters are important and that the skylight position parameter was unimportant; through the main effects analysis we can see that within those overall results there are areas of the percent glazed parameter space where decisions are critical, and other areas where, once pressed into that portion of design space, decisions are not as critical.

CONCLUSION

A (relatively) user friendly method for the design and analysis of high dimensional parametric building energy models has been demonstrated. The combination of effective tools for both the visualization and statistical analysis of the design space holds promise in enabling the creation of sustainable design processes that make use of the information rich early stage design spaces described herein. It is our expectation that such tools will do more than simply make quantitative assessment of variation available in early stage design. Current modes of practice in the sustainable design community, specifically the division of labor described in the introduction, tend to reinforce the perception that the resolution of the quantitative and qualitative aspects of a design are separate yet unfortunately related problems, and that the prioritization of one inevitably results in the neglect of the other. Our hope is that by creating simulated spaces where both aspects of a design can (to some extent) be evaluated, simultaneously, by an integrated design team, the binary subdivision of the larger design problem can be avoided in the interest of pursuing holistic solutions.

Still, the incorporation of such tools into actual design workflows remains dependent on the dissemination of tools currently available only in BES research labs, thus the study of actual design process "in the wild" remains necessary to gauge the real world effectiveness of such techniques. Furthermore, the use of these tools and techniques, cannot, perforce, occur in a vacuum, and although parametric CAD tools are in fact becoming commonplace in the design professions, the minimal understanding of statistical methods necessary for the appropriate interpretation of the results of the type of analysis described is not part of the typical engineer or architect's mental toolkit. Thus the development of effective tools remains only one, albeit critical, part of the larger problem of creating effective methods of designing a sustainable built environment.

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