Automated Design of Buildings: Need, Conceptual Approach, and Illustrative Example

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ABSTRACT

Historically, detailed building energy simulation programs have been used to either perform heating and cooling load calculations for HVAC equipment sizing purposes or to predict the whole building annual energy usage for evaluating a particular design. Based on user inputs that describe the building and imported weather data, these software programs simulate the hourly building performance over the course of a year, and provide outputs such as energy consumption by end use, demand, utility costs, etc. In this conventional approach, the building design parameters are essentially fixed by the user before the simulation is performed. Therefore, the standard practice is to use these programs for design analysis rather than design synthesis. The intent of the automated design methodology concept proposed in this paper is to use detailed building energy simulation programs in a different manner. Due to design constraints, aesthetic issues, program restrictions, or specific owner requirements, the optimal design may not be always desired. More valuable to the designer than determining the optimum is knowing the "latitude" s/he has in changing certain design variables while maintaining pre-selected desired performance criteria. The goal of the automated design methodology is thus to provide designers with a decision support tool rather than an optimization tool, i.e., a manner of generating numerous (in the hundreds) design alternatives which meet pre-stipulated performance criteria from which the designer can make the final selection for a particular project. Implementing such a methodology early in the design process will provide building professionals with a much larger solution set of possible designs options (which may not have been selected from intuition and experience alone). This paper describes the concept of automated design, lays the foundation for building such a methodology, and provides an illustrative example which begins to explore one possible approach of practically implementing the automated design approach.

PROBLEM STATEMENT

Designing buildings to be energy efficient is by no means a straightforward process. Building materials, building components, and building systems all have individual as well as interacting impacts on building energy consumption. The complexity of the design problem originates from the large number of variables involved, the dynamic nature of building loads and processes, and the intricacy of interaction effects among variables (Clarke, 1993). The choice of one design alternative can yield energy savings for one end-use while simultaneously resulting in an energy penalty for another end-use. Also, the amount of energy savings a particular design alternative can achieve is often dependent upon whether or not certain other energy saving strategies have already been implemented. Due to the ubiquitous nature of the design problem,

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evaluating energy efficient design alternatives can be computationally intensive. As a result of the complexity of the design problem, the intuition and experience of the designer is typically not enough to achieve high performance results from the building design. Also, the large number of variables usually guarantees unique design challenges for each project. Therefore, performance-based methodologies, using detailed simulations, for energy efficient design should be favored over simple prescriptive or "one-size-fits-all" approaches which are based heuristic knowledge. The design problem is further complicated by the fact that there will typically be some unknown or only partially defined variables, continuous information changes, and multiple "correct" or "satisficing" design solutions (Addison, 1988; Reddy, 2011).

OBJECTIVE AND SCOPE

The primary objective of automated design is to provide an automated, computer-based methodology that implements a currently available detailed energy simulation program to assist and improve the design synthesis of energy efficient buildings. Although design optimization is a popular topic, the automated design methodology should recognize that optimization may not be the goal of the designer. Due to design constraints (e.g., defined by cost restrictions, building energy code requirements, etc.), aesthetic issues, program restrictions, or specific owner requirements, the optimal design may not be desired or feasible. Also, from the designer's point of view, the mathematically optimal design may not be desirable because it may be too constrictive and it may limit creativity. More valuable to the designer than knowing the optimum solution is knowing the "latitude" or "degrees of freedom" they have in changing certain design variables while maintaining the desired performance criteria within the project constraints. Therefore, the goal of automated design should be a decision support tool allowing design synthesis rather than an optimization tool. This would provide designers with a way of generating numerous (in the hundreds) design alternatives, comprised of specific values for all design variables of interest, which meet pre-stipulated performance criteria from which the designer can make the final selection for a particular project. Implementing such a methodology early in the design process will provide building professionals with a solution set of possible designs that meet most, if not all, design criteria. Since detailed building energy simulation programs capture the complex interaction effects between design variables, the automated design methodology should highlight tradeoffs in selecting such variables and should generate solutions sets which may not have been selected from intuition and experience alone. This paper discusses the automated design concept, reviews the applicability of current analysis and design methods to automated design, and provides the foundation for the development of an automated design methodology.

AUTOMATED DESIGN CONCEPT

The key concepts being portrayed in this automated design concept paper include the following: (i) utilizing detailed building energy simulation programs for computer-aided design synthesis, (ii) generating a set of "satisficing" solutions rather than one unique solution, (iii) developing a decision-support tool compatible with design environments which allows the user to explore design "latitude" or "degrees of freedom", (iv) creating a learning tool which assists in developing the designers intuition rather than "brute force" methods which operate as a "black box", and (v) providing real-time feedback on how design decisions impact desired performance criteria. Figure 1 below graphically depicts the basic concept of automated design in the form of a proposed approach. The subsequent sections describe in more detail the various parts of the process.

Inputs and Outputs

The inputs and outputs of an automated design methodology differ fundamentally from those used in traditional building energy simulations. In the latter, inputs include all the design values that describe the building and its systems and outputs include energy consumption and costs. For the automated design methodology, however, many of the outputs of the building energy simulation become inputs specified as design objectives or performance criteria. Similarly, many of the inputs of the building energy simulation become outputs, i.e. solution sets of design variables.

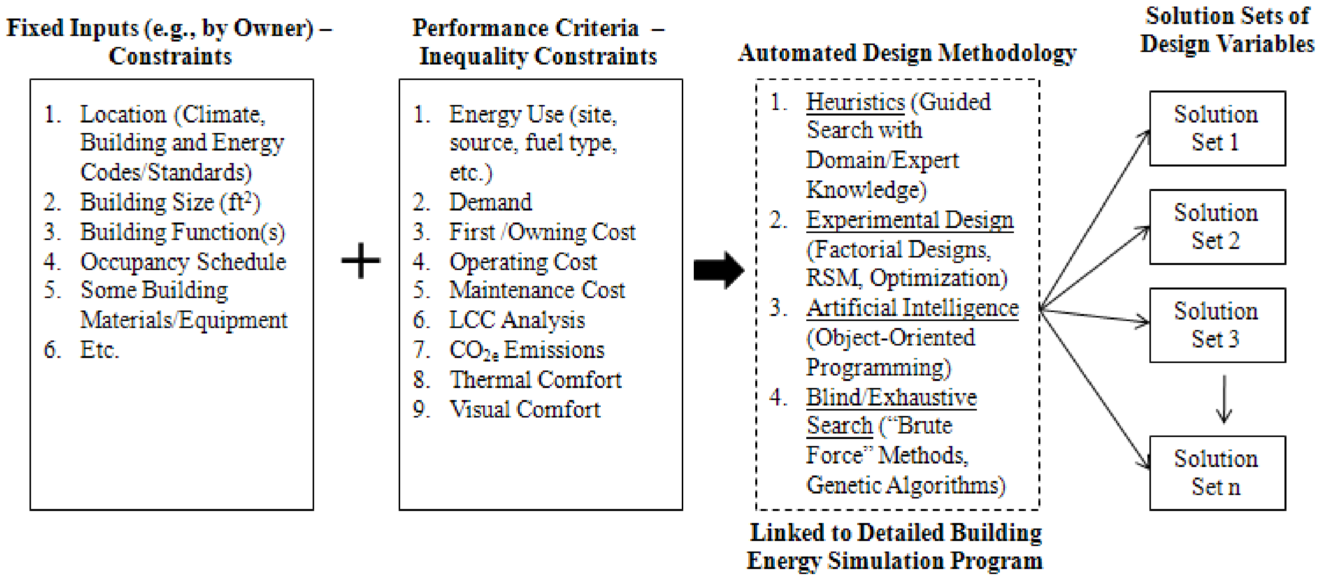

Figure 1 *Automated Design Proposed Approach Flow Chart*

Fixed Inputs and Performance Criteria. The inputs of the automated design methodology will consist of both fixed inputs and desired performance criteria. Fixed inputs are those which the designer has no control over. Many of the fixed inputs are determined at the very beginning of the design, by the owner for example, and can include building location (weather), building size, building function (which may determine some internal loads), occupancy and use schedules, and possibly some building materials or equipment. The other inputs are the performance criteria for the project. These are most likely inequality constraints such as maintaining an energy use intensity (e.g., kBTU/ft^2-yr) less than a certain value. Although the context of this paper focuses on energy consumption (annual, monthly, hourly, etc.), other criteria such as energy use by fuel type (e.g., electric vs. natural gas), electrical demand, greenhouse gas emissions, embodied energy of design, water use, etc. could be also included.

Solution Sets of Design Variables. The outputs of the automated design methodology are solution sets of design variables. Each "satisficing" solution set includes design attributes and components (i.e., values of independent variables) which satisfy the equality and inequality constraints specified by the fixed inputs and the performance criteria (Addison, 1988). The number of solution sets could be in the order of hundreds. The automated design methodology should hold the values of the independent variables in the solutions sets within theoretical and physical limits as well as practical limits (e.g., as defined by manufacturers, building and energy codes, etc.). The user should also be able to specify which independent variables for the automated design to vary in the generation of solution sets (i.e., not all possible design variables may be of interest in any given project). Independent variable transformations could be used in an intelligent way to reduce the number of variables that must be considered (i.e., create aggregate independent variables).

Once the user identifies the design variables of interest, i.e. those which can be varied to meet the desired performance criteria, the automated design methodology produces solutions sets as a result. Each set provides a different combination of the values of each design variable, each within their respective limits, which meet the equality and inequality constraints of that particular design problem. By determining multiple solution sets, the methodology gives the designer design freedom to choose the best option. Therefore, rather than simply restricting the designer to certain prescriptive values for certain design variables, the methodology should identify the designer's "degrees of freedom" or how much "latitude" they have in their design decisions with respect to desired performance criteria. For example, if while using response surface methodologies one discovers a “stationary ridge” relating two design variables, the designer could “walk” along that ridge while maintaining the desired response.

Integration with Design Environments

These solution sets could also take the form of “dynamic intervals” for each independent variable. The initial, i.e. maximum, length of each interval is defined by the pre-specified limits of that variable. As the user begins to select values of design parameters, the intervals for all the other parameters begin to change. It is within these resulting intervals that the designer is free to move (i.e., free to select the values of the remaining design variables) without stepping outside the bounds of the desired performance criteria. In a software environment, this could take the form of a visual aid or interactive graphic in which the designer can receive real-time feedback on how design decisions impact performance criteria. As the designer fixes certain variables, observing the resulting changes in the intervals of other variables will begin to illuminate the interactions that exist among those variables. For example, while designing/drafting, the program will provide the user with real-time feedback on energy consumption every time a change is made to opaque material or glazing material properties, equipment types, window area, building orientation, occupancy schedules, lighting power densities, floor plan dimensions, etc. With current energy simulation programs, which will most likely not be linked to a designer’s drafting program, one is limited to a trial-and-error type of analysis (that is assuming the time is taken to do another simulation every time a change is made to a certain variable). The hope is that real-time feedback will eliminate the trial-and-error approach of design.

The goal here will be to inform the uniformed and to lead designers away from traditional/conventional designs based on heuristics. Besides being a useful tool for experienced professionals, the intended audience should also be “non-experts” in energy-efficient building design. Similarly, architects using the tool will be able to see how their design decisions impact mechanical system design variables as well as overall building energy consumption which are difficult to do with current design practices. Architects generally see energy-efficient design requirements, e.g. from energy codes, as negative or detrimental to their design vision. Rather than having a mechanical engineer tell them what they cannot do, an automated design methodology could help bring to light the various trade-offs that the designer can make to still maintain the desired performance criteria. This, as a result, should help to promote creativity in the design process.

Possible Approaches to Automated Design

There are many potential strategies or analysis procedures which could be used for an automated design methodology including the following:

Heuristic Design – Knowledge-Based Expert Systems. Heuristic design is one of the most common techniques in the industry where design practices are based on successful previous projects or even past mistakes. The use of knowledge-based expert systems would be the extreme case of a heuristics approach where a search is guided by domain/expert knowledge. In a software environment, this involves developing a detailed knowledge base (e.g., database) for HVAC system and energy-efficient building design which has a user interface for designers to interact with. The knowledge base will be composed of first principles, HVAC fundamentals, surveyed knowledge of experienced designers, case studies, standards, codes, etc. Programming can then be used to link this knowledge base to detailed energy simulation programs, optimization programs, etc. Some detailed energy simulation programs are a form of these knowledge-based systems because they have a fairly sophisticated system of default values that are a function of building type or system type selected. Maor (2002), Brothers (1988) and Shams et al. (1994) all discuss the use of knowledge-based expert systems in the design of HVAC systems.

Design of Experiments. Experimental design methodologies (Montgomery, 2009; Reddy, 2011) such as factorial designs, response surface methods, regression techniques, etc. seem to be a very good fit with the concept of automated design. Such methods are typically light in computational effort and have a transparency such that they can help designers learn about building dynamics rather than blindly producing solutions. Design of experiments techniques for building design problems are also found in the literature (Hou et al., 2006; Chlela et al., 2000).

Artificial Intelligence. There are many design and analysis techniques that could fall under the umbrella of "artificial intelligence". The topic is too broad to be covered here in detail and can be found in publications such as Maor (2002). Such methods, however, have significant potential in the building design industry, especially when combined with software-based design environments (the publications of Pohl and collaborators from Cal Poly Obispo are prime examples) of an intelligent software design environment that can assist human designers in the design of buildings.

"Brute-force" Methods. "Brute-force" methods such as exhaustive searches (e.g., Christensen et al. 2005) and genetic algorithms (e.g., Caldas and Norford 2003) have their advantages and are certainly suitable building design optimization (i.e., they can handle discrete variables, multiple objectives, large number of variables, etc.). However, from the perspective of the designer, they generally require large run-times and result in tools that "blindly" produce solutions. This may have limited benefit in assisting the design process by further educating the designer.

ILLUSTRATIVE EXAMPLE – AUTOMATED DESIGN USING DESIGN OF EXPERIMENTS

Experimental design methods were utilized as a first attempt at illustrating one approach to developing an automated design methodology. Specifically, an effort was made to develop response surface models for building energy use based on a batch of simulations using DOE-2.2. The medium sized office commercial reference building developed by the Department of Energy was used as the basis for these simulations. The basic features of the building include: 53,630 ft^2, three floors, 1.5 aspect ratio, 33% window-to-wall ratio, gas furnace heating, unitary DX cooling, VAV with electric reheat terminal units, etc. The idea was to begin with selecting a small number of design variables, use an experimental design (e.g., factorial design, central composite design, etc.) to set up a batch of simulations to run in DOE-2.2 and then develop response surfaces relating the various design variables to the response. The initial goal was to identify factor interactions and relationships and identify the form of surfaces generated (e.g., linear, 2nd order, multi-modal, etc.). The overall regression model (i.e., whole building annual energy use as a function of the variables of interest) could then be used in place of the detailed building energy simulation program to predict the value of the response as design variables are being changed. The next step in an automated methodology remains unclear. Since traditional graphical analysis methods tend to fail after just a few variables, an intelligent way of displaying the various variable interactions and their impact on the response needs to be created. In addition, a method of identifying sets of solutions (i.e., combinations of design variable values) which meet the desired values of the response needs to be developed.

Selection of Independent Variables to Analyze

The independent variables selected to be included in the response surface model should be those which have important impacts on energy use as well as those that are simply important to designers (e.g., variables that are commonly involved in design decisions). The values or ranges of each variable to analyze in the experimental design should be realistic and typically encountered values but they should not be restricted to the values in the energy code. The desire of the designer may be to see what trade-off options (design "latitude") are available if the designer wants to go below code in a certain variable(s). Performance trade-offs are similar to performance-based standards. The goal is to go beyond the prescriptive "one-size-fits-all" approach. A list of 30 specific design variables of interest was developed based on the following criteria: the frequency that they appear in the reviewed literature (e.g., Reddy and Maor 2006, Lam and Hui 1996), heuristic knowledge of how they impact building energy use, and assumptions of how important they are in terms of typical design decisions made by designers. Since at this stage it is not known how to tackle the complex problem of developing an automated design methodology, a smaller subset of these variables was selected in a first attempt to illustrate the concept.

The subset of variables selected to be analyzed first were some of the more common "architectural" design variables listed in Table 1 along with their ranges. Further research should begin to add more design variables related to architecture, internal loads, scheduling, and HVAC systems. A central composite experimental design was used to set up the simulations to run with different combinations of values of the five variables being considered. With five (5) variables at two (2) levels each, a central composite design with axial points and two center points yields 44 factorial runs or simulations.

Table 1: Design Variables and their Ranges for Illustrative Example

Design Parameter	Range
Lighting Power Density (LPD)	0.8 – 1.5 [W/ft^2]
Window Shading Coefficient (SC)	0.2 – 0.7
Exterior Wall R-Value	7.8 – 27 [hr-ft^2-°F/BTU]
Window U-Value	0.26 – 1 [BTU/hr-ft^2-°F]
Window-to-Wall Ratio (WWR)	0.1 – 0.5

DISCUSSION AND CONCLUSION

After selecting the independent variables to analyze and performing the batch simulations in DOE2.2, a statistical analysis software package was used to develop the response surface models from the data. The results discussed below are for the Madison, WI weather file. A quick glance at the results showed little curvature for whole building annual electrical energy use (kWh) and whole building annual natural gas energy use (kBTU) for the five variables analyzed (WWR, Window U-Value, Wall U-Value, SC, and LPD). In general, the response surfaces for all combinations of the five design variables, in the range of values analyzed, were planes with optimal values at one of extreme points. This can be due to the fact that the variables selected do not have very interesting interactions or because many interactions between variables are with respect to one end-use or one season which becomes damped or hidden within the whole building annual energy use value. This issue of selecting the right response variable requires more research and attention. When looking at both the electricity and gas response one can observe some interactions. For example, a reduction in LPD results in electrical energy savings but a penalty in gas consumption due to the reduction of beneficial lighting heating load in the winter. Figure 2 is an example of these response surfaces; the relationship between window shading coefficient and lighting power density is shown. Figure 3 shows the same surfaces as contour plots.

Figure 4 is a fictitious plot that illustrates the concept with a surface of curvature. If a one performance criterion is to have an annual natural gas consumption of less than 116,500 kBTU, then the hatched areas on the plot show the combinations of SC and LPD which meet that criterion. However, these combinations may only apply to this one performance criterion and with these two design variables. The hatched areas will most likely change once other design variables are considered and if other performance criteria are desired. This is where such graphical analysis methods fail unless they are dynamic. An automated design methodology should be able to handle a large number of design variables and generate combinations of those variables that meet multiple performance criteria.

As discussed, the concept of automated design can quickly become very complex. There are many possible approaches to pursuing an automated design methodology and all may have their own advantages and disadvantages. Some combination of techniques will most likely provide the best solution. Future research efforts should first try to reduce the scope of the automated design problem into more manageable pieces. This paper illustrated the concept and laid the foundation upon which future work can continue to develop and refine these ideas into a successful automated design methodology.

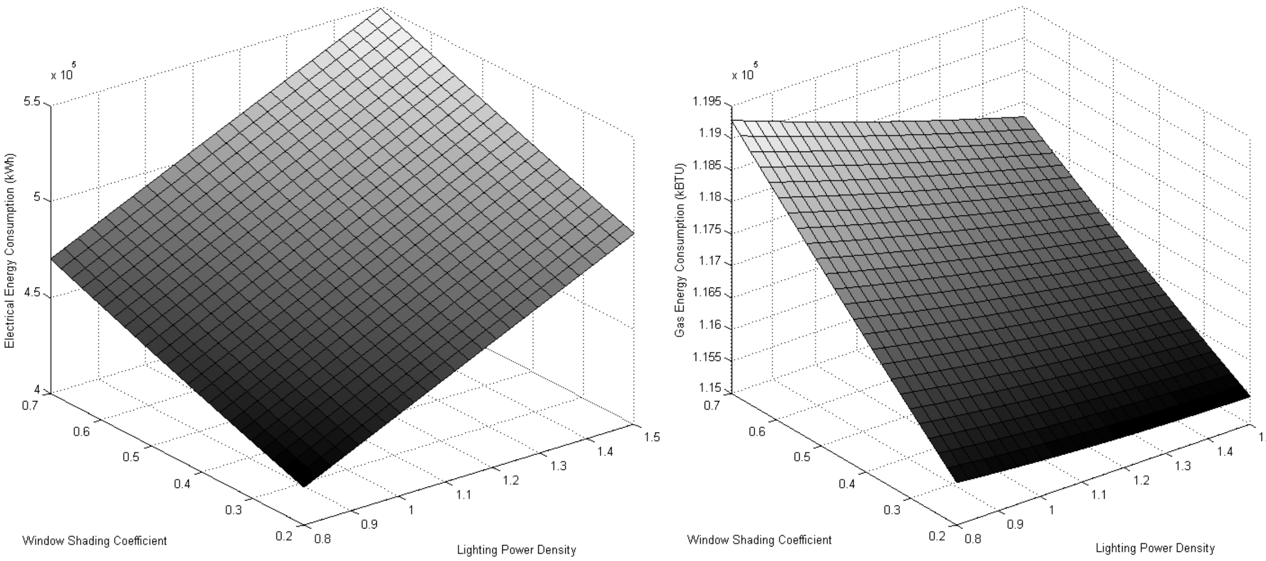

Figure 2 *Annual Electrical Energy Use (kWh) and Natural Gas Energy Use (kBTU) Surface Plots for Shading Coefficient vs. Lighting Power Density*

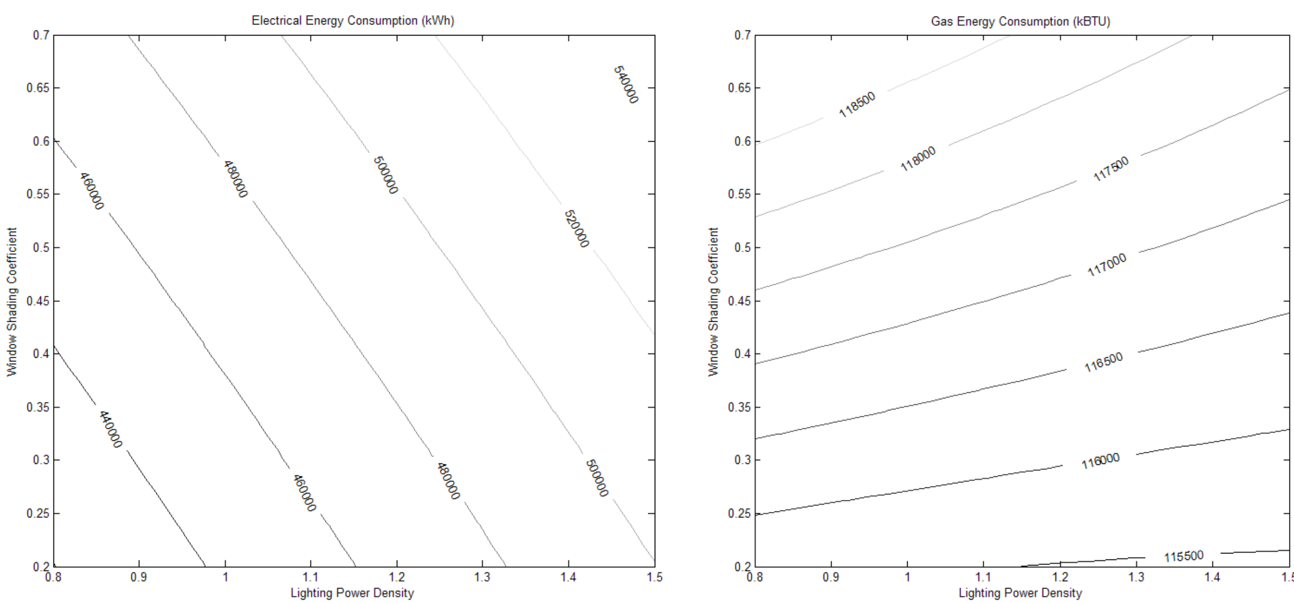

Figure 3 *Annual Electrical Energy Use (kWh) and Natural Gas Energy Use (kBTU) Contour Plots for Shading Coefficient vs. Lighting Power Density*

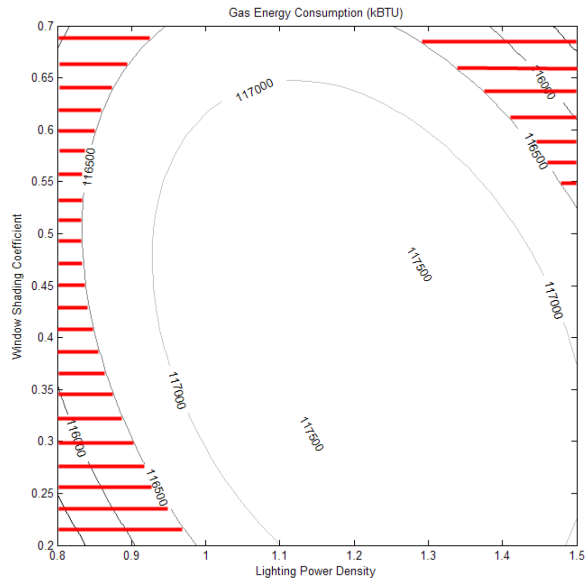

Figure 4 *Contour Plot of SC vs. LPD Showing Variable Combinations which meet a Desired Performance Criterion*

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