



All the ways of meeting a target: Calculating a solution surface using GenOpt

Brian Coffey¹, Dan Tuhus-Dubrow², Madhav Munshi³
¹Independent, ²EnerNOC, ³Atelier Ten

ABSTRACT

Energy efficiency consultants are often asked to find a variety of ways of meeting an energy target, from which the client would select the most suitable by considering installation costs, aesthetics and other concerns. Clients are usually presented with just a few discrete options, but in most cases there are actually infinite ways of meeting the target. Given an n -dimensional space of options defined by n design parameters, the set of options that exactly meet a particular target is generally a surface of $n - 1$ dimensions. This paper describes methods to calculate a grid of solution points on this surface by selecting one design parameter x_i , defining a grid of values for the remaining design parameters ($x_j, \forall j \neq i$) and for each grid point using GenOpt to find the value of x_i that exactly meets the target (if a solution exists for that grid point). The technique may also be used to describe trade-offs between design parameters around some reference point. A case study is used herein for illustration. The result is a more comprehensive description of options, and can lead to a richer interaction between designer and analyst, and more designer insight into the energy-related aspects of their project.

INTRODUCTION

Building simulation tools have gained popularity through their applications in code compliance and building design rating systems. However, they are often considered as a once-per-design or once-per-phase exercise, rather than being more integral to the design process in the way that CAD software often is. As such, much of simulation's potential for aiding in low-energy building design is not being used.

This may be due in part to a discrepancy between forward simulation (taking a fixed building description and weather file and calculating energy consumptions) and the types of questions that designers tend to be grappling with. In particular, a designer can often benefit from a better understanding of the energy trade-offs between different design parameters; there is a complex relationship between some set of design parameters and energy consumption metrics, and the focus of their questions is often more on the relationship between design parameters than

it is on how any one particular configuration of design parameter values relates to the energy metrics. A single simulation run, however, is just for a single set of parameter values, and building simulation users manually operating GUIs tend to settle into finding energy metric results of some set of discrete "energy efficiency measures" (each a particular set of parameter values), compared to a "baseline" (an agreed upon set of parameter values, usually defined by code or the rating system).

Much more is possible when the building simulation user shifts their attention from manually running single simulations to intelligently orchestrating many simulations to investigate particular aspects of the problem. A simulation may be conceived as a complex function that relates design parameters to energy metrics; the goal of the analyst is to map out important parts of that function, and to do so in such a way that clarifies the nature of the design problem at hand. Filling this role could simply mean mapping the energy consumption impact of increasing or decreasing a particular parameter (or set of parameters) over some range of values. It could mean using sensitivity analysis to find which variables have the most impact on energy use. And/or it could involve using an optimization algorithm to find the lowest energy configuration within some region of the search space.

This paper describes a concept and calculation procedure that can be added to this set of analytical tools for using simulation to clarify design decisions. It places the focus squarely on the trade-offs between design parameters, given a desired energy metric value.

In the interest of keeping the paper brief, the authors have elected not to provide a full explanation of optimization; there is a large volume of literature available on the use of single- or multi-variable optimization with building simulation (e.g. (Wetter and Wright 2003; Wetter and Wright 2004; Wright and Alajmi 2005; Charon, Athienitis, and Pasini 2005; Magnier and Haghghat 2010)). What is described in this paper is not optimization per se, but rather the calculation of a continuous surface within the design space that contains all the possible ways of meeting a particular energy metric target - a calculation that happens to require the iterative use of optimization. In the methods herein, GenOpt (Wetter 2009) is used



for these optimizations, but any optimization tool or algorithms could be used. To the authors' knowledge, such a calculation procedure has not been described in the building simulation literature. The methods are first described in general below, followed by an illustrative case study and discussion.

METHODS

Given some set of design parameters $x_i, i = 1..n$, and a particular energy metric of interest y , a building simulation may be considered generically as shown in Equation 1. The energy metric may be annual site energy consumption, or annual energy cost, or summer cooling load, or anything similar.

$$y = f_{sim}(x_1, x_2, \dots, x_n) \quad (1)$$

Consider a target y_{target} , such as some percent more efficient than an ASHRAE 90.1 baseline, or simply some $z \text{ kWh/m}^2 \cdot \text{yr}$, or similar. Given y_{target} , we wish to define all of the design configurations $[x_1, x_2, \dots, x_n]$ for which Equation 2 is true.

$$\begin{aligned} &\text{the set of all vectors } [x_1, x_2, \dots, x_n] \\ &\text{such that } f_{sim}(x_1, x_2, \dots, x_n) = y_{target} \end{aligned} \quad (2)$$

That is, we wish to define all of the possible ways of meeting the energy target. (From the result of this begins the process of selecting the most suitable option(s) by considering installation costs, aesthetics and other concerns.) Note that if any of the parameters x_i are continuous variables, there are usually an infinite number of possible ways of meeting the target: the solution is generally a surface of $n - 1$ dimensions. The goal is to solve for this surface.

Because the building simulation f_{sim} is generally nonlinear and complex, and because we usually do not have direct access to the underlying equations, we cannot derive this solution surface analytically. However, we can approximate it to any arbitrary level of precision by solving for it over a grid as follows.

- Select one design parameter x_i
- Define a grid of values for the remaining design parameters ($x_j, \forall j \neq i$)
- For each grid point use an optimization algorithm to find the value of x_i that exactly meets the target (if a solution exists for that grid point)
- Repeat the above three steps, if more precision in the surface definition is desired, for the remaining design parameters x_i

The computational time required is a function of the simulation run time, the optimization algorithm efficiency and precision, and the number of grid points, as discussed in more detail below. It is recommended that the process be carried out first for a relatively coarse grid, the results graphed and interrogated, and then after necessary debugging or refinement of either the model, constraints or optimization algorithm, re-run the study for a higher resolution grid.

Visualization of the solution is very important. If $n > 3$, then it cannot be visualized all at once, but rather can be viewed through interactive 3D graphs (with the axes able to change and fixed values for the unshown parameters) or animations.

It should be noted that many design parameters may be discrete variables rather than continuous (for example, insulation level is often dependent on wall thickness, which is often constrained by what material dimensions are commonly available). With discrete parameters, the solution surface is generally not continuous. This can be dealt with in one of two ways: (1) if there is at least one continuous variable, that one variable can be used as the selected design parameter x_i , and the grid of values for the remaining parameters can be set to only consider feasible values for those parameters - the results are then to be interpreted as a set of lines rather than as a continuous surface; or (2) perform the analysis with the fiction that all of the discrete variables are continuous, and calculate the solution surface - this divides the search space into two volumes, on one side of the solution surface is the set of all points that more than meet the target, on the other side is the set of all points that do not meet it. Approach (1) would provide specific points that exactly meet the target, whereas approach (2) would show a volume of possible ways of exceeding the target (only some of which are possible given the discrete variables); which approach is best for a particular design project depends on the problem under consideration, the psychologies of the design team members and how the analyst relates to them.

Selecting design parameters to be interrogated may require some judgement on the part of the analyst. Including too many parameters may make the visualization process too cumbersome for the client and may take effort away from where it should be focused, too few may leave out important aspects of the design. Some parameters may be best lumped together, such as using a common insulation level for all walls instead of considering each separately. One may also wish to include parameters as 'design parameters' that may not be directly manipulable by the design team but yet have significant effects on the influences of other parameters, as a way of helping the design team with decision-making under uncertain conditions. The simulation tool itself may also play a role in selecting the

design parameters, as some parameters (in the case study below, for example, the infiltration air change rate) may be much more straightforward to model and discuss than individual parameters or sets of parameters (e.g. air leakage rates for walls, windows, etc) that have similar effects. In short, as with most any good design analysis process, there is a bit of an art to framing the analysis in order to make it as meaningful as possible to the design team and the design problems at hand.

CASE STUDY: PCM VS INSULATION

As part of the design development phase for a small environmental education center in Pittsburg, PA, an analysis was undertaken to aid the client in deciding if they should consider embedded phase change materials (PCM) in the building. A simple whole-building EnergyPlus model (Figure 1) had already been created and set up for parametric analysis during the schematic design phase, where it was used to map the relative performance of a variety of design options and to highlight sensitive design parameters, to aid the design team as they worked towards a net-zero energy building. This model was modified to include a PCM layer on the interior of the opaque portions of the envelope¹. The thickness of the PCM layer was treated as a design parameter. Because of the climate and the low internal loads in this building, the annual heating load is much more significant than the cooling load; the total annual heating load was used as the model output of interest.

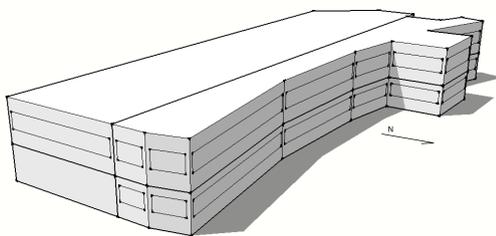


Figure 1: EnergyPlus model geometry

The first stage of analysis simply mapped out the annual heating load as a function of PCM thickness, holding the various other design parameters (e.g. insulation thickness, infiltration rate, window-to-wall ratio, various window properties, etc) fixed at some values, and then repeating the process for different fixed values. Two examples of the resulting diminishing-returns curves are shown in Figure 2.

¹Other PCM locations were analyzed as well, but for simplicity only these results are considered here. Various types of PCM were also considered, but the results discussed here are only for one particular commercially-available PCM material with a phase-change temperature of approximately 23°C.

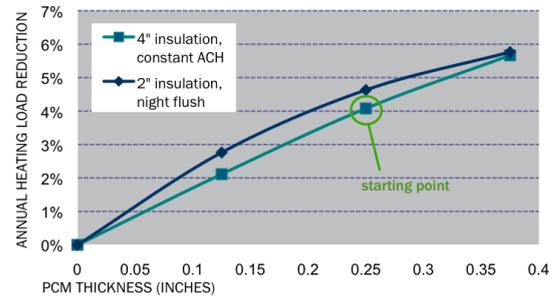


Figure 2: Annual heating load savings vs PCM thickness

The analysis suggested that the most cost-effective PCM thickness to consider would likely be in the range of 1/4", and that it could reduce the annual heating load by roughly 5% (depending on the values of the other design parameters). The analysis also showed the annual heating load to be very sensitive to the insulation thickness and the infiltration rate (as expected given the previous sensitivity analysis in schematic design). As such, it would be useful to understand and quantify the trade-offs between these three design parameters. For example, the client may want to know how much added insulation (or decreased infiltration) would provide the same annual heating load reduction as a certain added thickness of PCM. These trade-off questions can be answered very generally for a target annual heating load level by calculating a solution surface as described above.

Consider the point highlighted in Figure 2, which has a PCM thickness (x_{pcm}) of 1/4", and some fixed values of the remaining design parameters, including an insulation thickness (x_{ins}) of 4" and an infiltration rate (x_{ach}) of 0.20 air changes per hour. The annual heating load associated with this point will be used as our target (y_{target}).

The goal is then to map out all of the possible values of the design parameters² vector $[x_{pcm}, x_{ins}, x_{ach}]$ that produce the desired output y_{target} . The design parameter x_{pcm} is selected arbitrarily as the first for consideration, and a grid of values for $[x_{ins}, x_{ach}]$ is defined as shown in Figure 3. For each point in this grid, an optimization is carried out to find the value of x_{pcm} that minimizes the difference between the model output (y_{model}) and y_{target} . The end of the EnergyPlus bat file is modified to call a script that calculates $(y_{model} - y_{target})^2$ as the objective function, and GenOpt is used for the optimization with the GPS-Hookes-Jeeves algorithm. The existing open-source java code in SimCon (Coffey 2011a) is used to set up and run the grid of optimizations, although this could also be eas-

²Note that the air change rate is in fact a function of other parameters (some of which, such as construction quality, are only indirectly manageable by the design team), but it is much more straightforward to model and to explain than the alternatives.

ily done through custom scripting. The resulting solutions over the grid are shown as points in Figures 4 and 5, and interpolated as a 3D surface in Figure 4 or as a series of 2D lines in Figure 5. The starting point highlighted in Figure 5 is the same point as was highlighted in Figure 2. The 3D graph shows the surface as a whole, while the flat description of 2D lines makes for easier reading of quantities.

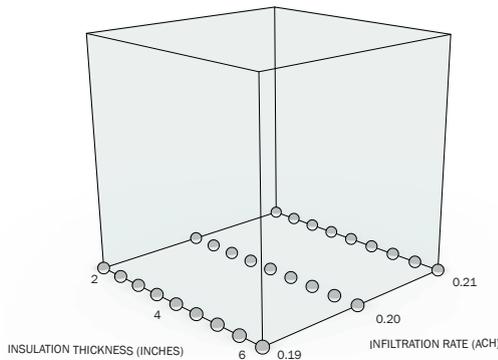


Figure 3: Grid points

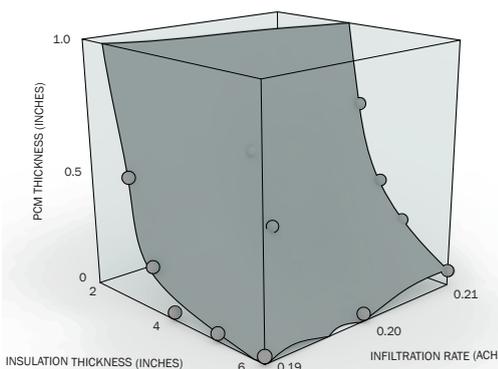


Figure 4: Solution surface in 3D

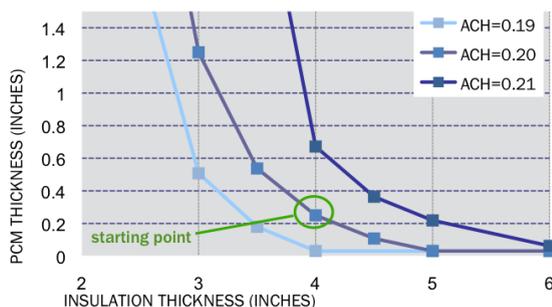


Figure 5: Solution surface viewed as lines in 2D

The graphs of the solution surface show a number of important analytical results concerning the potential use of PCMs in this particular project. Where the curves in Figure 5 intersect with the horizontal axis are instructive: increasing insulation thickness from 5" and not using the PCM would result the same annual heating load as the case with 4" insulation and 1/4" PCM; similarly, decreasing the infiltration rate from 0.20 ACH to 0.19 ACH would have the same effect on annual heating load as the 1/4" PCM. Also note the general shapes of the curves: if the insulation thickness was decreased to less than 3" or 4" (depending on the infiltration rate), then a very large amount of PCM would be required to produce the same annual heating load. As such, the advice to the clients is to not think of the PCM as a substitute for their existing insulation plans of roughly 4", but rather as an addition, and to compare the estimated costs of 1/4" of the PCM to those of an additional 1" of insulation or of a 5% decrease in infiltration.

Note that the volume above the surface is where the annual heating load would be lower than the target level, and the volume below the surface is where it would be greater than the target. In this analysis, the PCM thickness and insulation thickness were treated as continuous variables, but as other aspects of the design solidify (and as a brand of PCM gets selected), either or both of these two may actually be only be feasible for particular discrete values (such as a PCM thickness of either exactly 0.25 inches or 0.5 inches). If this turns out to be the case, the analysis is still useful in that it divides the possible options into those that do better than the target (ie. those above the surface) and those that do worse than it. It could also be easily re-run, with x_{ach} selected as the first variable considered, and the grid of values for $[x_{pcm}, x_{ins}]$ set only for feasible values of those two parameters.

DISCUSSION

This approach can be used in a wide variety of applications. In early design phases it can be used with simplified models to map out possible strategies for meeting a particular energy target, and/or used to investigate the feasibility of different targets. It can also be used in working out design details, such as those shown in the example case study.

The selection of an appropriate grid is an art that requires some understanding of the problem at hand and a knowledge of the computational time requirements and trade-offs in the configuration. How fine the grid must be depends on the problem at hand, and on what level of precision is needed to aid the design. In general, it is best to start with a relatively coarse grid, and then refine it where necessary after investigation of the results. The grid need not be regular, and as shown in the case study above, it can often be rather coarse and still be very useful.



The computation time required ($t_{computation}$) is a function of the simulation time (t_{simAve}), the precision and efficiency of the optimization algorithm (which determines the average number of simulations per optimization, O_{optAve}), and the number of grid points ($N_{gridPoints}$), as shown in Equation 3.

$$t_{computation} = N_{gridPoints} \cdot O_{optAve} \cdot t_{simAve} \quad (3)$$

If a regular grid is being used, and c_i is the number of values of considered for variable x_i , then $N_{gridPoints}$ is defined as shown in Equation 4.

$$N_{gridPoints} = \prod_{i=1}^n c_i \quad (4)$$

In the case study, each simulation required approximately 3 min (the model was simple, but PCM simulations in EnergyPlus are slow), the average optimization required approximately 50 simulations, and there were $9 \cdot 3 = 27$ grid points, so approximately 135 processor-hours were required. In this case, the computations were completed on a single two-processor machine, allowed to run first overnight and then, after some grid refinement, over a weekend. The solutions for the grid points can be easily computed in parallel, which makes it amenable to cloud computing; at \$0.10 per processor-hour (the approximate current cost for small users of cloud virtual machines), the example would have cost about \$13.50. For problems with a higher number of parameters n , the computation time requirement grows exponentially: this dilemma is nearly identical to that faced in defining lookup table approximations to model predictive control (Coffey 2011b), which has been shown feasible for problems with 5-6 parameters with 5-10 values each, but more parameters or finer grids would likely require trade-offs in optimization precision or model complexity.

The result of using this approach is a more comprehensive description of the design options available. What then becomes a key part of the analyst's role is translating the information in this solution surface into understanding among the design team. If this task is performed well, then the approach of calculating solution surfaces like this can lead to a richer interaction between designer and analyst, and provide the design team with more insight into the energy-related trade-offs of their project.

CONCLUSION

A computational technique is presented to define a $n - 1$ dimensional solution surface that describes all of the ways of exactly meeting a particular energy target given n design parameters. The solution surface shows trade-offs between design parameters. As such, it can be used to help navigate the design process towards better design decisions.

REFERENCES

- Charron, R, A Athienitis, and M Pasini. 2005. "Integrated Design and Optimization Issues for Zero Energy Solar Homes." *The Second CDEN International Conference on Design Education, Innovation, and Practice*.
- Coffey, B. 2011a. "SimCon download." <ftp://ftp.pwgs.c.ca/rpstech/Controls/MPC/SimCon/>.
- Coffey, B. 2011b. "Using Building Simulation and Optimization to Calculate Lookup Tables for Control." *PhD Thesis, University of California Berkeley*.
- Magnier, L, and F Haghghat. 2010. "Multiobjective optimization of building design using TRNSYS simulations, genetic algorithm, and Artificial Neural Network." *Building and Environment* 45:739-746.
- Wetter, M. 2009. "GenOpt: Generic Optimization Program." <http://gundog.lbl.gov/GO/>.
- Wetter, M, and J Wright. 2003. "Comparison of a Generalized Pattern Search and a Genetic Algorithm Optimization Method." *Proceedings of IBPSA, Eindhoven, Netherlands*.
- Wetter, M, and J Wright. 2004. "A comparison of deterministic and probabilistic optimization algorithms for nonsmooth simulation-based optimization." *Building and Environment* 39:989-999.
- Wright, J, and A Alajmi. 2005. "The Robustness of Genetic Algorithms in Solving Unconstrained Building Optimization Problems." *Proceedings of the 9th International Building Performance Simulation Association (IBPSA) Conference, Montreal, Canada*.