Proceedings of BS2013:
13th Conference of International Building Performance Simulation Association, Chambéry, France, August 26-28

Optimal Selection of Building Components Using Sequential Design via Statistical Surrogate Models

Rui Zhang, Fei Liu, Angela Schoergendorfer, Youngdeok Hwang, Young M. Lee and Jane L. Snowdon
IBM T. J. Watson Research Center, Yorktown Heights, NY 10598, USA

ABSTRACT

Choosing the optimal combination of building components that minimize investment and operational costs is a topic of great importance in the building simulation community. Optimization using simulation tools, i.e., *EnergyPlus*, becomes computationally expensive for traditional search approaches. An additional challenge is the complexity of the input parameter space, which is usually very large and contains both continuous and discrete variables. In this paper, we present a novel approach to address both of these problems. The key idea of the proposed approach is to first build a statistical surrogate model for the energy simulation model and to then update the surrogate model based on the concept of sequential design of experiments. We demonstrate the proposed approach using a case study of a live retrofit project for Building 661 at the Navy Yard of Philadelphia, USA. Results show that the statistical surrogate model allows for fast evaluation of the building's energy consumption, and the sequential design reduces the computational cost by requiring a smaller number of runs of the energy simulation model.

INTRODUCTION

Building envelope is main source of heat loss/gain, and hence has great impact on building heating/cooling energy consumptions. Therefore, choosing the optimal combination of building envelope components that minimizes investment and operational cost is a topic of great importance to the building simulation community. Traditional approaches often require a massive number of evaluations of energy simulation models such as *EnergyPlus*, EnergyPlus (2011). The major challenge of such approaches is high computational cost, especially in a realistic environmental context, as the search space is usually very large. In addition, the set of input parameters often contains both continuous and discrete variables, as most variables in real envelope design problems are discrete in nature. For example, there are only a finite number of types of glass materials available, which take finitely many values in each defining feature. Moreover, the different properties of glass are not independent of each other and can only take on a given set of combinations.

In this paper, we present a novel approach to address these challenges. The key idea of the proposed approach is to build a statistical surrogate model for the energy simulation model and update this model using new observations based on a sequential design of experiments. At the beginning of the algorithm, the energy simulation model is executed on an original space-filling design in order to build a statistical surrogate model in the form of a response surface defined on the input space of the energy simulation model. An expected improvement function then guides the search for the optimal combination in a sequential design step: A new design point will be defined as the vector of input parameter values that maximizes a predefined expected improvement function. The energy simulation model is then executed at the new design point and the surrogate model is updated to incorporate the result at the new design point. The algorithm iterates between the surrogate model building step and the sequential design step until the increase of the expected improvement function becomes negligible. We demonstrate the proposed approach using a case study of a live retrofit project for Building 661 at the Navy Yard of Philadelphia, USA, and show that the statistical surrogate model allows for fast estimation of the building's optimal energy consumption by reducing the number of energy simulation model runs required.

RELATED WORK

Solving optimization problems in the design and operation of energy efficient buildings has attracted a range of research efforts. See, for example, Asadi et al. (2012), Huchtemann and Müller (2012), Fesanghary, Asadi, and Geem (2012), Pang et al. (2012), Hazyuk, Ghiaus, and Penhouet (2012), Stazi, Mastrucci, and Munaf (2012) and Ellis et al. (2006). With increasing complexity of building systems, advancements in building simulation tools, and fast growth of computing capability, more and more research efforts focus on simulation-based optimiza-

tion. For example, the *Generic Optimization Program* (GenOpt) developed by Wetter (2004) implemented several search algorithms that work with building simulation programs. In Wetter and Wright (2004), the authors further compare the performance of nine optimization algorithms including direct search algorithms (e.g., coordinate search), stochastic population-based algorithms (e.g., a genetic algorithm), a hybrid particle swarm Hooke-Jeeves algorithm and a gradient-based algorithm. They conclude that the hybrid particle swarm Hooke-Jeeves algorithm yields the greatest reduction in their cost function, however, the computing cost is extremely high. The computational cost of building simulation programs also poses challenges in the control of building operations. As noted in Zhu et al. (2012), the intensive computation involved in the simulation makes on-line decision making infeasible. Although the two-stage scheme proposed in the paper facilitates decision making process, the off-line stage of the approach, which relies on an exhaustive search algorithm, can be very time consuming. Most studies point out that building energy simulation is expensive, yet there is a lack of efficient methods which can reduce this simulation cost.

In this paper, we propose a novel approach to overcome the computational complexity involved in the simulation models. Our approach is largely based on the statistical surrogate modeling ideas in statistical literature (Sacks and Wynn 1989, Santner, Williams, and Notz 2003, Kennedy and O'Hagan 2001, Bayarri et al. 2007a, Bayarri et al. 2007b). A simulation model is essentially a model describing an input-output relationship. As the model gets exceedingly complex, the simulation model is often treated as a "black box". Sacks and Wynn (1989) proposed to model the response of the simulation model nonparametrically by a stochastic process. For scalar output, the Gaussian response surface approach, adopted from kriging in the spatial statistics (Cressie 1993), is a typical approach for building a surrogate model. A Gaussian process is assumed as the prior distribution of the simulation model. Given a collection of runs obtained by executing the simulation model, applying the Bayesian updating mechanism of learning, we obtain the posterior distribution of the simulation model. The posterior distribution is then used as a surrogate model to the simulation model, i.e., at any untried input values, we can obtain the posterior distribution of the corresponding simulation model ouput. We remark that the surrogate model provides not only a mean estimate of the simulation output, but also the associated uncertainty at the new input.

The proposed approach is also closely related to the design of computer experiments, which concerns the selection of input parameters at which the computer model shall be executed. The use of the nonparameteric model for surrogate modeling necessitates space-filling designs such as maximin distance designs and Latin Hypercube designs (Box, Hunter, and Hunter 1978, McKay, Beckman, and Conover 1979, Johnson, Moore, and Ylvisaker 1990). In fact, the performance of the resulting surrogate models largely depends on the distance between an arbitrarily selected point and the training points in the input space. Space filling designs are derived to minimize such distances (Bursztyn and Steinberg 2006). Another related concept is the sequential design of computer experiments. Under the sequential design strategy, inputs are selected sequentially so that improvements over the current optimal input are expected to be large. A sequential design typically requires fewer runs of the simulation model, and is particularly suitable in the context of building simulation models given the related computational cost. See MacKay (1992), Cohn (1996), Jones, Schonlau, and Welch (1998) and Gramacy and Lee (2009) for more details on this topic.

METHOD

Problem Statement

The live retrofit of Building 661 on the Philadelphia Navy Yard was chosen as case study of the optimal building enclosure design using sequential design via statistical surrogate models. The objective is to minimize energy consumption, specifically, Energy Use Intensity (EUI), which is defined as energy use per floor area. The historic building features a shared open space at the back with gross area of about $1600m^2$, and a two-story space in the front with gross area of about $800m^2$ for each floor. After the retrofit, the building will house personnel of the EEB Hub (Energy Efficient Building Hub – established by the US Department of Energy (DOE) as an Energy Regional Innovation Cluster), and will function as a living laboratory for tools and methods that are intended to transform the building industry's current fragmented serial method into integrated team efforts. The building model is shown in Figure 1. The building at the center with pitched roofs and windows is Building 661. Three immediate neighbouring buildings are also presented in the figure and modeled in the simulation model as shading surfaces.

In the search of the optimal envelope design, we consider a high dimensional variable space that comprises alternative materials for the external wall insulation, roof insulation, different glazing types and different infiltration levels. The variables under consideration in this study and their corresponding ranges are listed in Table 1. The insulation materials' R values are obtained from manufacturers' product catalogues. The upper bound of the wall insulation thickness is the thickness required to obtain an R value of R-60. The thickness range of the roof insulation

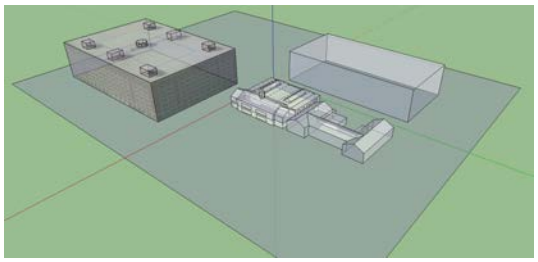

Figure 1: SketchUp model of Building 661 and surrounding buildings.

is based on the thickness required to achieve an overall R value of R-5 to R-90. The infiltration range is selected based on infiltration values in DOE reference building models for offices. The properties of the glazing materials are obtained from the LBNL Windows 7 software, which contains a database of 2695 types of glass available from manufacturers. The variables related to glass are taken as categorical variables, and can only take the combination of values represented among the 2695 types. Since optical properties of glass are interrelated, constraints on these variables are also defined.

The formulation of our optimization problem is defined as follows:

$$\begin{aligned} \underset{\mathbf{x}}{\text{minimize}} \quad & EUI(\mathbf{x}) \\ \text{subject to} \quad & x_7 + x_8 \leq 1, \\ & x_7 + x_9 \leq 1, \\ & x_{10} + x_{11} \leq 1, \\ & x_{10} + x_{12} \leq 1, \\ & x \succeq L,\ x \preceq U, \end{aligned}$$

where $\mathbf{x} \in \mathcal{X}$, $\mathcal{X} \subset \mathbb{R}^p, p = 15$ is the vector of independent variables, as listed in Table 1. $EUI : \mathcal{X} \to \mathbb{R}$ is the cost function and is computed by *EnergyPlus*, given input vector $\mathbf{x}$. $L, U \subset \mathbb{R}^p$ are the lower and upper bounds of the variables, which are listed in Table 1.

Surrogate Model

Computational cost is the major limitation for efficiently employing *EnergyPlus* or any other simulation model for building design and retrofit. Computation time of building energy simulation is dependent on the complexity of building configurations such as building geometry and mechanical systems, and the algorithm used in the simulation program. Simulation time for a single model typically ranges from a few minutes (4 to 5 minutes) to more than an hour. In our demonstration model, we used a model of a two-story building with simple mechanical systems in *EnergyPlus*, and the run time is 9 minutes. An exhaustive search that would run *EnergyPlus* for all possible combinations of materials/components (2695 possible feature combinations for glass material, combined with continuous values for wall and roof materials) is not feasible. To overcome this difficulty, we rely on a statistical surrogate modeling approach.

Table 1: The variable space for optimal building envelope design, and the ranges of the variables.

Variable x_i	Variable Description	Lower bound	Upper bound
Wall insulation:			
x_1	Thickness (m)	0.05	0.526
x_2	R Value ($K \cdot m^2/W$)	0.51	2.21
Roof insulation:			
x_3	Thickness (m)	0.091	0.343
x_4	R Value ($K \cdot m^2/W$)	0.51	2.21
x_5	*Infiltration:* ($m^3/s \cdot m^2$)	0.00012	0.0012
Glazing:			
x_6	Thickness (mm)	0.038	26.67
x_7	Solar transmittance(%)	0.0003	0.91
x_8	Front solar reflectance (%)	0.03	0.83
x_9	Back solar reflectance (%)	0.03	0.81
x_{10}	Visible transmittance (%)	0.0	0.92
x_{11}	Front visible reflectance (%)	0.01	0.70
x_{12}	Back visible reflectance (%)	0.01	0.72
x_{13}	Front infra-red hemispherical emissivity(%)	0.01	0.96
x_{14}	Back infra-red hemispherical emissivity (%)	0.01	0.96
x_{15}	Conductivity ($W/m \cdot k$)	0.13	1.01

EnergyPlus is deterministic, i.e., executing a model twice with the same input value yields two identical output values. This is an important perspective we need to take into account in the surrogate model. A popular statistical approach to handle computationally expensive deterministic simulation models is the Gaussian Response Surface Approximation (GASP) method (Sacks and Wynn 1989). It treats the simulation model as an unknown function describing the input-output relationship between model parameters and EUI. A Gaussian process is then assigned as the prior distribution of the unknown function. Initial runs of the simulation model are selected according to a specified design criterion. See the next section, "Initial Design", for more details of the criterion on the design. The corresponding outputs, together with their inputs are then used to update the posterior distribution of the unknown function. This will yield a response surface of the simulation model over the entire input parameter space, which provides the predictive distribution of the simulation model at any model input. The response surface, or the predictive distribution of the simulation model, is referred to as a statistical surrogate model to the simulation model. Since evaluating the response surface is very fast, we may use the surrogate model for further analysis, instead of the computationally expensive simulation model.

Let p be the number of input parameters the user specifies for the *EnergyPlus* model. Denote the feasible space

for the input parameters of the model by $\mathcal{X}$, $\mathcal{X} \subset \mathbb{R}^p$. Let $Y(\mathbf{x}_i)$ denote the *EnergyPlus* model output, where $\mathbf{x}_i = (x_{i1}, \ldots, x_{ip}) \in \mathcal{X}$. The prior distribution for the response $Y(\cdot)$ takes the following form

$$Y(\cdot) \sim \mathrm{GP}(\mu, \sigma^2 c(\cdot,\cdot)),$$

where μ is the mean, σ^2 is the variance, and $c(\cdot,\cdot)$ is the correlation function of the Gaussian process. The Gaussian process is widely used to model data observed over space. It has the property that the joint distribution of $Y(\cdot)$ at a finite set of points $\mathbf{x}_1, \ldots, \mathbf{x}_n$ has a n-dimensional multivariate normal distribution, for which the covariance between $Y(\mathbf{x}_i)$ and $Y(\mathbf{x}_j)$ is equal to $\sigma^2 c(\mathbf{x}_i, \mathbf{x}_j)$. In this paper, we use a separable form of the correlation function defined as

$$c(\mathbf{x}_i, \mathbf{x}_j) = \exp(-\sum_{k=1}^{p} \beta_k \mid \mathbf{x}_{ik} - \mathbf{x}_{jk} \mid^{\alpha_k}).$$

Let $\mathbf{X} = (\mathbf{x}_1, \ldots, \mathbf{x}_n)$ be a design of the input parameters (e.g., a collection of input vectors) and $\mathbf{Y}$ be the vector of corresponding outputs. Consider a specific input $\mathbf{x}$ at which $Y(\mathbf{x})$ has not been observed. Let ρ be the n-dimensional vector with the ith element $c(\mathbf{x}, \mathbf{x}_i)$ and Σ be the $n \times n$ matrix with the (i, j) element $c(\mathbf{x}_i, \mathbf{x}_j)$. The posterior predictive distribution for $Y(\mathbf{x})$ can be written as

$$[Y(\mathbf{x}) \mid \mathbf{X}, \mathbf{Y}] \sim \mathrm{N}(\widehat{\mu}(\mathbf{x}), \hat{s}^2(\mathbf{x})),$$

where

$$\widehat{\mu}(\mathbf{x}) = \Sigma^{-1}\rho'\mathbf{Y}, \quad \text{and} \quad \hat{s}^2(\mathbf{x}) = \sigma^2\left(1 - \rho'\Sigma^{-1}\rho\right). \quad (1)$$

We estimate the model parameters in the Gaussian process using `mlegp` in R (R Core Team 2012). Mean and variance in (1) can be evaluated at all possible input vector at negligible computational cost. This Gaussian process represents a response surface which models the input output relationship, providing a statistical surrogate model to *EnergyPlus*.

Initial Design

To build the initial surrogate model, we need to obtain an initial design for *EnergyPlus*. When there is no prior information on the functional behavior of the response, it is appealing to spread out design points uniformly over the input space, as interesting features of the simulation model are equally likely to appear across the input space. As such, a *space-filling* design is appropriate for initial planning of an energy simulation.

For $\mathbf{x}_i, \mathbf{x}_j \in \mathbb{R}^p$, let d be the Euclidean distance defined by

$$d(\mathbf{x}_i, \mathbf{x}_j) = \left(\sum_{k=1}^{p} |x_{ik} - x_{jk}|^2\right)^{1/2}. \quad (2)$$

A criterion function based on d is

$$\phi_\lambda(\mathbf{X}) = \left[\sum_{\mathbf{x}_i, \mathbf{x}_j \in \mathbf{X}} d(\mathbf{x}_i, \mathbf{x}_j)^{-\lambda}\right]^{1/\lambda} \quad (3)$$

with a positive integer λ (Morris and Mitchell 1995). Note that a design $\mathbf{X}^*$ minimizing (3) for $\lambda = \infty$ is called *maximin distance design* (Johnson, Moore, and Ylvisaker 1990) and satisfies

$$\min_{\mathbf{x}_i, \mathbf{x}_j \in \mathbf{X}^*} d(\mathbf{x}_i, \mathbf{x}_j) = \max_{\mathbf{X} \subset \mathcal{X}} \min_{\mathbf{x}_i, \mathbf{x}_j \in \mathbf{X}} d(\mathbf{x}_i, \mathbf{x}_j). \quad (4)$$

For more on the design criterion, see Santner, Williams, and Notz (2003) and references therein.

Inspired by Stinstra et al. (2003), we obtain an initial design for a given λ by first generating a random design and then sequentially improving the overall design via optimizing one individual input combination ("run") while fixing the remaining runs. For a design $\mathbf{X}$ of n runs, define $\mathbf{X}_i$ to be a design of $n-1$ runs deleting the ith run, and define $\mathbf{X}_i(\mathbf{x})$ as design $\mathbf{X}_i$ augmented by a new input $\mathbf{x}$. It is easy to see that $\phi_\lambda(\mathbf{X}_i(\mathbf{x}))$ is a function of $\mathbf{x}$ only, as the remaining $n-1$ runs are fixed. Now we have n reduced S_i problems

$$S_i : \arg\min_{\mathbf{x} \in \mathcal{X}} \phi_\lambda(\mathbf{X}_i^*(\mathbf{x})) \quad (5)$$

Let $\mathbf{x}^*$ be the solution of S_i and $\mathbf{X}_i^*$ the design $\mathbf{X}_i$ augmented by $\mathbf{x}^*$. Now the design is constructed by Algorithm 1:

Algorithm 1

Define initial solution $\mathbf{X}$;
$\phi_{\text{old}} := \phi_\lambda(\mathbf{X})$;
while improvement $> \varepsilon$ **do**
  do improvement $:= 0$;
  for $i = 1$ to N **do**
    solve S_i;
    improvement $:= \phi_{\text{old}} - \phi_\lambda(\mathbf{X}_i^*)$;
    $\phi_{\text{old}} := \phi_\lambda(\mathbf{X}_i^*)$;
    $\mathbf{X} := \mathbf{X}_i^*$;
  end for
end while

This algorithm is a modified version of Stinstra et al. (2003). Each S_i is easily solved as only one $\mathbf{x}_i$ needs to be updated at a time. Attainment of a global optimum cannot be guaranteed due to the heuristic nature of the algorithm, but it proves to perform well in practice. To illustrate, a two-dimensional design of 15 runs obtained by Algorithm 1 is presented in Figure 2 where $\mathcal{X} = \{\mathbf{x} : x_1 + x_2 \leq 1\}$ with $\lambda = 20$. The selection of λ greatly depends on the specific problem, such as the dimension and size of the design. With a small value of λ, the algorithm tends to reduce ϕ quickly during initial steps, but struggles to improve in later steps of the algorithm, while the algorithm

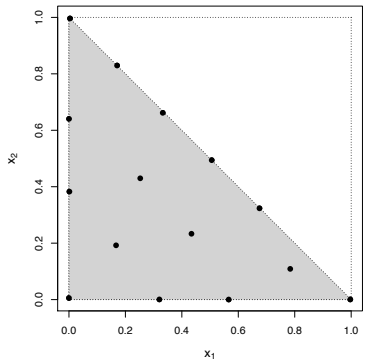

Figure 2: Projection of a two-dimensional design of 15 runs obtained by Algorithm 1, where $\mathcal{X} = \{\mathbf{x} : x_1 + x_2 \leq 1\}$.

converges more slowly in the beginning steps with larger λ. To construct the initial design for our case study, λ was chosen to be 20. The constrained optimization for S_i is performed using `constrOptim` in R (R Core Team 2012).

Sequential Design

We utilize the response surface of the surrogate model to solve the global optimization problem of finding the optimal combination of building components. The search space is explored according to a strategy that balances local and global search. On the one hand, the search should explore component combinations that promise the lowest EUI according to the surrogate model. Following this strategy would however easily result in a local minimum close to observed locations in the search space. Globally, on the other hand, it may be preferrable to explore areas in the search space where uncertainty about the response behavior is still great. The concept of *expected improvement* (Jones, Schonlau, and Welch 1998) balances these two contradicting arguments and, for a given input vector $\mathbf{x}$, is defined as the following expectation:

$$E\big[I(\mathbf{x})\big] = E\big[\max(y_{\min} - Y, 0)\big], \tag{6}$$

where $y_{\min} = \min\{\mathbf{Y}\}$ is the smallest function value among all observed responses. In the case of a Gaussian process response surface, this expectation can be computed as

$$\begin{aligned} E\big[I(\mathbf{x})\big] = (y_{\min} - \widehat{\mu}(\mathbf{x}))\Phi\Big(\frac{y_{\min} - \widehat{\mu}(\mathbf{x})}{\hat{s}(\mathbf{x})}\Big) \\ + \hat{s}(\mathbf{x})\phi\Big(\frac{y_{\min} - \widehat{\mu}(\mathbf{x})}{\hat{s}(\mathbf{x})}\Big) \end{aligned} \tag{7}$$

using the parameter estimates derived according to (1). Here, Φ is the distribution function of a standard normal distribution, and ϕ is the corresponding density function.

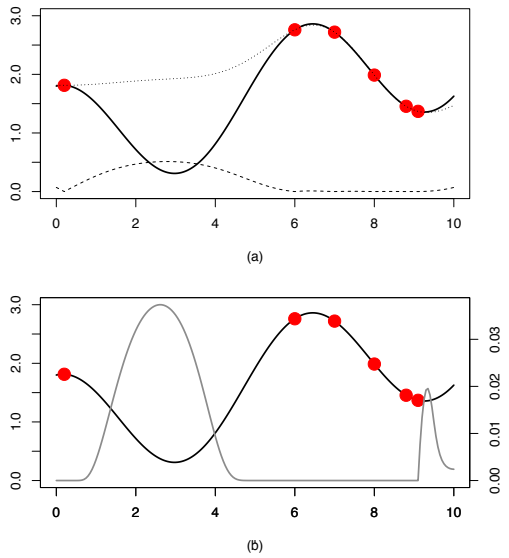

Figure 3: Fitted model (dotted line) of an unobserved function (solid line) plotted along standard error estimates for fitted values (dashed line, Figure (a)) and contrasted with expected improvement (grey line, Figure (b)).

As an example, Figure 3 visualizes the tradeoff between local minima and uncertainty about the fitted surrogate model for a one-dimensional function f. Red dots represent the observed responses that have been obtained by evaluating f at selected sample points. Based on the fitted response surface (dotted line) only, we might expect the minimum of f to be at $x = 9.4$. However, our uncertainty about the response, expressed as the standard error of the fitted value $\widehat{\mu}(\mathbf{x})$, is greatest between 2 and 4 (dashed line in Figure 3(a)). The expected improvement according to (7) is represented as a grey line in Figure 2.b. Balancing uncertainty about the response and a small value of $\widehat{\mu}(\mathbf{x})$ leads the search algorithm to suggest a new exploration point at $x = 2.6$, the point at which the expected improvement is maximized.

To find the $\mathbf{x}^*$ which maximizes the expected improvement, we may use readily available functions for optimization of continuous functions with constraints, such as the function `optim()` in R (R Core Team 2012), using the `method = "L-BFGS-B"` option for the Brouden, Fletcher, Goldfarb and Shanno method with box constraints (Byrd et al. 1995). In this particular application, however, we encounter variables that are discrete, and we only allow for $K = 2695$ distinct combinations of these variables ("slices"). The combination of variables that leads to the greatest expected improvement is thus found in two stages. Let $\mathcal{X}^{(k)}$ be the feasible space of parameter values in which the variables corresponding to the discrete glass characteristics are fixed at combination k, $k \in 1, \ldots, K$. In

the first stage, for each k, we maximize expected improvement over all continuous variables. In the second stage, we then compare maximum expected improvement across all slices and choose the combination with the greatest expected improvement.

The optimal combination of building components is found in an iterative fashion, as outlined in Algorithm 2. After fitting the surrogate model to the observations obtained at the initial design $\mathbf{X}$, the optimization stage finds the new design point $\mathbf{x}^*$ that maximizes the expected improvement across all slices. EnergyPlus then evaluates the model at the new design point and the new response $Y(\mathbf{x}^*)$ is added to the data set. The surrogate model is refit to the augmented data, and the steps of optimization, model simulation and surrogate model rebuild are iterated until one of several stopping criteria is met. If the expected improvement of a new variable combination is (a) less than a small fraction t_a (for our application, we chose 1%) of the current minimum EUI or (b) smaller than a pre-defined meaningful threshold t_b (we chose 0.05), we terminate the search. For practical reasons and limitations on total computation time of the entire search, the search may also be stopped if it has not resulted in any actual improvement of EUI in a given number of simulations, or has exceeded an acceptable number of iterations.

Algorithm 2

$\mathbf{Y} = EUI(\mathbf{X})$;
StoppingCriterion := FALSE;
while StoppingCriterion = FALSE **do**
  fit surrogate model $Y|\mathbf{X},\mathbf{Y}$;
  for $k = 1$ to K **do**
    $\mathbf{x}_k^* := \arg\max_{\mathbf{x}\in\mathcal{X}^{(k)}} E\left[I(\mathbf{x})\right]$;
  end for
  $\mathbf{x}^* := \arg\max_{\mathbf{x}\in\{\mathbf{x}_1^*,\ldots,\mathbf{x}_K^*\}} E\left[I(\mathbf{x})\right]$;
  if $E\left[I(\mathbf{x})\right] < y_{\min}\cdot t_a$ **or** $E\left[I(\mathbf{x}^*)\right] < t_b$ **then**
    StoppingCriterion := TRUE;
  else
    $y^* = EUI(\mathbf{x}^*)$;
    $\mathbf{X} = \mathbf{X}(\mathbf{x}^*)$; $\mathbf{Y} = (\mathbf{Y}, y^*)'$;
  end if
end while

RESULTS SUMMARY

The algorithm described in the previous sections runs in R (R i386 2.15.1) and EnergyPlus (7.1.0) on a Windows 7 machine with Intel Core 2 Duo CPU @ 2.40GHz processor. With such configuration, the simulation of the Building 661 model takes 9 minutes. To start, 100 initial design points were generated, and after 95 iterations, the algorithm reached convergence criterion as expected improvement is less than 0.05, as is shown in Fig.4. Therefore, in total 195 iterations were needed for our approach to reach convergence, which is far less than the typical iteration number of 300 to 500 (Wetter and Wright 2004).

Figure 4: The maximum expected improvement over iterations.

To show the performance of our algorithm in finding the minimum, we first define a benchmark value, which is computed as following: for each variable x_i, we used the median value, denoted as x_i^b, to form the input value set for EnergyPlus to compute the EUI. And the resulting EUI value is used as the benchmark value, which is $EUI(x^b) = 224.29$. The cost function value found by our optimal algorithm is $EUI(x^m) = 151.12$, which is a 32.6% reduction in cost function from the benchmark value. The input variables x^m, where the minimum was found, are shown in Table 2.

Table 2: The variable space for optimal building envelope design, and the ranges of the variables.

Variable x_i	Variable Description	Value at minimum
Wall insulation:		
x_1	Thickness (m)	0.40
x_2	R Value ($K\cdot m^2/W$)	0.90
Roof insulation:		
x_3	Thickness (m)	0.34
x_4	R Value ($K\cdot m^2/W$)	0.72
x_5	*Infiltration:* ($m^3/s\cdot m^2$)	0.00044
Glazing:		
x_6	Thickness (mm)	13.48
x_7	Solar transmittance(%)	0.28
x_8	Front solar reflectance (%)	0.56
x_9	Back solar reflectance (%)	0.07
x_{10}	Visible transmittance (%)	0.49
x_{11}	Front visible reflectance (%)	0.27
x_{12}	Back visible reflectance (%)	0.31
x_{13}	Front infra-red hemispherical emissivity (%)	0.89
x_{14}	Back infra-red hemispherical emissivity (%)	0.14
x_{15}	Conductivity ($W/m\cdot k$)	0.98

Furthermore, we also formulated the same problem us-

ing the Genetic Algorithm (GA) in Matlab, MATLAB (2012). And the parameters used in the GA are as follows: we used a population size of 20, a maximum of 50 generations, and a probability for recombination of 0.5. Several attempts were tried, and GA does not come to a converged stage.

CONCLUSION

This paper presents an efficient and effective method for solving optimization problems in the field of building design, which often depends on computationally expensive simulations of various types. The presented method consists of three parts: an initial design of experiment, the construction of a statistical surrogate model, and a sequential design approach for the search of an optimal solution. The method was applied to find the optimal combination of building envelopes that minimize energy consumption under the Philadelphia climate context for a two-story building. Results show that the method is efficient in the sense that it requires fewer evaluations of the building model than are commonly necessary. For the demonstration problem setting with a combination of 15 continuous and categorical variables, the method finds the optimal solution with expected improvement of 0.05 EUI within 195 iterations.

REFERENCES

Asadi, E., M. G. da Silva, C. H. Antunes, and L. Dias. 2012. "A Multi-objective Optimization Model for Building Retrofit Strategies Using TRNSYS Simulations, GenOpt and MATLAB." *Building and Environment* 56:370 – 378.

Bayarri, M., J. Berger, G. Garcia-Donato, F. Liu, J. Palomo, Paulo, Sacks R., Walsh J., J. D., Cafeo, and R. Parthasarathy. 2007a. "Computer Model Validation with Functional Outputs." *Annals of Statistics* 35:1874–1906.

Bayarri, M. J., J. O. Berger, R. Paulo, J. Sacks, J. A. Cafeo, J. Cavendish, C.-H. Lin, and J. Tu. 2007b. "A Framework for Validation of Computer Models." *Technometrics* 49:138–154.

Box, G. E. P., W. G. Hunter, and J. S. Hunter. 1978. *Statistics for Experimenters: An Introduction to Design, Data Analysis, and Model Building*. New York: Wiley.

Bursztyn, D., and D. M. Steinberg. 2006. "Comparison of Designs for Computer Experiments." *Journal of Statistical Planning and Inference* 136:1103–1119.

Byrd, R. H., P. Lu, J. Nocedal, and C. Zhu. 1995. "A Limited Memory Algorithm for Bound Constrained Optimization." *SIAM Journal on Scientific and Statistical Computing* 16:11901208.

Cohn, D. A. 1996. "Neural Network Exploration using Optimal Experimental Design." In *Advances in Neural Information Processing Systems*, Volume 6, 679–686.

Cressie, N. A. C. 1993. *Statistics for Spatial Data*. New York, NY: Wiley.

Ellis, P. G., B. T. Griffith, N. Long, P. Torcellini, and D. Crawley. 2006. "Automated Multivariate Optimization Tool for Energy Analysis." *in Proceedings of the SimBuild 2006 Conference, Cambridge, MA*.

EnergyPlus. 2011. *EnergyPlus Documentation*.

Fesanghary, M., S. Asadi, and Z. W. Geem. 2012. "Design of Low-emission and Energy-efficient Residential Buildings Using a Multi-objective Optimization Algorithm." *Building and Environment* 49:245 – 250.

Gramacy, R. B, and H. K. H. Lee. 2009. "Adaptive Design and Analysis of Supercomputer Experiments." *Technometrics* 51:130–145.

Hazyuk, I., C. Ghiaus, and D. Penhouet. 2012. "Optimal Temperature Control of Intermittently Heated Buildings Using Model Predictive Control: Part II - Control Algorithm." *Building and Environment* 51:388 – 394.

Huchtemann, K., and D. Müller. 2012. "Simulation Study on Supply Temperature Optimization in Domestic Heat Pump Systems." *Building and Environment*, pp. 327–335.

Johnson, M. E., L. M. Moore, and D. Ylvisaker. 1990. "Minimax and Maximin Distance Designs." *Journal of Statistical Planning and Inference* 26:131–148.

Jones, D. R., M. Schonlau, and W. J. Welch. 1998. "Efficient Global Optimization of Expensive Black-box Functions." *Journal of Global Optimization* 13:455–492.

Kennedy, M., and A. O'Hagan. 2001. "Bayesian Calibration of Computer Models (with discussion)." *Journal of the Royal Statistical Society, Series B* 63:425–464.

MacKay, D. J. C. 1992. "Information-based Objective Functions for Active Data Selection." *Neural Computation* 4:589–603.

MATLAB. 2012. *version 8.0.0.783 (R2012b)*. Natick, Massachusetts: The MathWorks Inc.

McKay, M. D., R. J. Beckman, and W. J. Conover. 1979. "A Comparison of Three Methods for Selecting Values of Input Variables in the Analysis of Output from a Computer Code." *Technometrics* 21:239–245.

Morris, M. D., and T. J. Mitchell. 1995. "Exploratory Designs for Computational Experiments." *Journal of Statistical Planning and Inference* 43:381 – 402.

Pang, X., M. Wetter, P. Bhattacharya, and P. Haves. 2012. "A Framework for Simulation-based Real-time Whole Building Performance Assessment." *Building and Environment* 54:100 – 108.

R Core Team. 2012. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. ISBN 3-900051-07-0.

Sacks, J., Welch W. J. Mitchell T. J., and H. P. Wynn. 1989. "Design and Analysis of Computer Experiments." *Statistical Science* 4:409–435.

Santner, T. J., B. J. Williams, and W. Notz. 2003. *The Design and Analysis of Computer Experiments*. New York, NY: Springer-Verlag.

Stazi, F., A. Mastrucci, and P. Munaf. 2012. "Life Cycle Assessment Approach for the Optimization of Sustainable Building Envelopes: An Application on Solar Wall Systems." *Building and Environment* 58:278 – 288.

Stinstra, E., P. Stehouwer, D. Hertog, and A. Vestjens. 2003. "Constrained Maximin Designs for Computer Experiments." *Technometrics* 45:340–346.

Wetter, M. 2004. "Simulation-Based Building Energy Optimization." Ph.D. diss., University of California at Berkeley.

Wetter, M., and J. Wright. 2004. "Comparison of Deterministic and Probabilistic Optimization Algorithms for Nonsmooth Simulation-based Optimization." *Building and Environment* 39:989–999.

Zhu, J., L. Shen, R. Yin, and Y. Lu. 2012. "A Two-stage Simulation-based On-line Optimization Scheme for HVAC Demand Response." *in Proceedings of the SimBuild 2012 Conference, Madison, WI.*