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A methodology for meta-model based optimization in building energy models

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ABSTRACT

As building energy models become more accurate and numerically efficient, model-based optimization of building design and operation is becoming more practical. The state-of-the-art typically couples an optimizer with a building energy model which tends to be time consuming and often leads to suboptimal results because of the mathematical properties of the energy model. To mitigate this issue, we present an approach that begins by sampling the parameter space of the building model around its baseline. An analytical meta-model is then fit to this data and optimization can be performed using different optimization cost functions or optimization algorithms with very little computational effort. Uncertainty and sensitivity analysis is also performed to identify the most influential parameters for the optimization. A case study is explored using an EnergyPlus model of an existing building which contains over 1000 parameters. When using a cost function that penalizes thermal comfort and energy, 45% annual energy reduction is achieved while simultaneously increasing thermal comfort by a factor of two. We compare the optimization using the meta-model approach with an approach using the EnergyPlus model integrated with the optimizer on a smaller problem using only seven optimization parameters illustrating good performance.

1. Introduction

Currently, model-based analysis of buildings is predominately used for code compliance such as LEED certification, and some minor scenario studies in architectural and engineering firms, or in the research or academic community in a more detailed context. As building energy models become more advanced, accurate, and easy to use, model-based building design is becoming more widespread. In order to be useful in an industrial context, the design cycle iteration time for a building design and operation scenario (DOS[1]) must be very fast. This cycle includes not only simulation time, but analysis of its results and action based on these results.

One form of analysis that is currently performed with building energy models is optimization, which investigates how the DOS of a building influences key measurables of the building (e.g. thermal comfort, energy consumption, life cycle costs) and seeks a DOS that meets some optimal combination of these (often weights are used to indicate different levels of importance of each variable in the cost function). In the building energy modeling literature, there are examples of this procedure using methods ranging from finding this optimal in a detailed but ad hoc way (e.g. [1,2]) to advanced numerical methods that automatically find the optimum which are reviewed below.

Numerical optimization of energy models first arose in the 1970s and continues to be an active research area. The anatomy of the optimization process typically includes an optimizer and a function which it is trying to optimize. This function is usually an energy model, that once given a certain building DOS, a cost or objective value is produced through numerical simulation (usually for an entire year of typical weather and environmental conditions). Software environments for optimizing building energy models exist for this purpose that are either specific to an energy simulator [3], or more generic [4]. The goal of the optimizer is to intelligently determine new DOSs (based on previous attempts), in such a way that the final DOS has converged to an optimal value.

In the building energy modeling community, derivative-free (DF) optimization routines [5], which do not require gradient information from the simulation model are typically used. The reason that these methods are used is because derivative information, if

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[1] We use the term *design and operation scenario* (DOS) to describe the architectural design of the building as well as specific strategies and considerations for its operation (e.g. scheduling).

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obtained numerically from the model, is often not accurate because a continuous or differentiable objective function does not exist (see [6–8]). This often results in the optimizer converging to local optimal points, for example in [9] where many optimal design alternatives were found in the optimization process. There are many specific types of DF methods and in the building energy community, two types: genetic algorithms and pattern search are often employed in the buildings community and are discussed below.

Genetic algorithms (GA) are a class of mathematical optimization approaches that imitate natural biological evolution in which the process of inheritance, mutation, selection, and crossover is utilized to determine the best solution. The likelihood of converging to a suboptimal solution (local minima) is reduced in this method because the search considers a population of solutions and not a descent along a gradient. Examples of the use of GA-based optimization in building energy modeling include [10] which seeks an optimal building envelope design based on life cycle costs, or [9] that studied a case where building form (12 orientations), materials (16 choices) and HVAC operation (6 load control steps) were optimized. Similarly, Wright et al. [11] used a GA-based optimizer to optimize energy cost and occupant comfort by varying 63 control variables (for a single day). A simple model of a single zone with an HVAC system operating open loop using only outside air was used for this example.

The pattern search (PS) method is another valuable DF optimization technique that searches along coordinates in an intelligent way to find the minimum of an objective function. This method has been used in [12] where the software GenOpt [4] was used to investigate how 10 parameters (9 parameters relating to the hydronic system, and 1 envelope parameter) influence energy consumption, capital cost, and comfort. Additionally, in [13] 30 design variables were optimized using pattern search (Hooke–Jeeves) through the simulation of the model approximately 5000–10,000 times. In this case, the model was a simple set of algebraic equations that did not take very long to simulate.

In a recent and very thorough study [14], both GA and PS based methods (with some modification) were compared on a large set of test functions as well as an EnergyPlus building energy model. The conclusion was that both methods find a similar objective function value (energy consumption), but with a different combination of parameter values. This highlights that it is not always the best practice to use only one optimizer on a problem that has multiple minima. This is especially relevant if the building model is complex and the number of optimization parameters is large.

In most of the cases listed above, the number of evaluations of the numerical simulation of the energy model is in the 1000s for a single cost function (another set of simulations would be needed if for instance the weights in the cost function were changed even slightly). As discussed in [10], the computational cost limits the ability to study large sets of optimization parameters. For instance, in [12], approximately 400 simulations were needed to find the optimal of 10 parameters, and this sequence was repeated 10 times for different water supply temperatures. In addition to this, in [14] the number of model simulations needed to find an optimum was approximately 3000, but 5 runs were performed to capture the influence of different initial conditions (seeds) of the optimizer, and in [7], 13 parameters were optimized taking on the order of 600 extensive EnergyPlus simulations. Because of this, time becomes an important issue and in many cases, a full model of a building (created in one of many simulation packages like eQUEST, EnergyPlus, or TRNSYS) is avoided and a simpler model is created (as in [15,13], among others).

To alleviate some of the issues with optimization time, in this paper we present a method that begins by characterizing the building energy model by varying all of the input parameters of the model within a certain range around its baseline design. Once these simulations are complete, a meta-model (a 'model of a model') is fitted to the simulated data and an optimization algorithm is applied to either this model or a reduced form of it. This approach has been performed in other building energy studies to predict energy usage [16] and to perform sensitivity analysis [17]. The kernel method was also used in [18] where over a year's worth of building energy data was used to create an accurate model that is capable of predicting excursions that may be due to faulty conditions.

In the meta-model scenario, the optimization itself takes on the order of a minute on a typical desktop or notebook computer. Because of this, many cost functions, optimization algorithms, or subsets of optimization parameters can be investigated without performing additional and exhaustive simulations.

A schematic of this approach is presented in Fig. 1, and the following sections discuss in detail each step. Following this, we demonstrate this approach using an EnergyPlus model as a case study including the results for multiple optimization scenarios (different cost functions, different parameter sets, and different optimizers). Most of the steps in this flowchart were performed using the integrated Global Sensitivity and Uncertainty Management and Optimization software [19]. We compare the meta-model approach with the traditional full order model approach in one case where the number of parameters in the optimization set is small (7 optimization parameters), and illustrate that computation time is decreased while maintaining similar convergence properties.

2. Approach

2.1. Repeated sampling

The goal of the sampling is to expand the prediction of a building energy model from one single baseline DOS to many cases around it. This is done by varying the parameters of the model within a range around their baseline value. There are multiple ways to specifically define this variation, including the Monte Carlo method, which randomly selects these samples. Unfortunately, when doing this, the parameter space is sampled non-uniformly. To avoid this issue, we use a quasi-Monte Carlo (deterministic) sampling approach that provides samples that are more uniformly distributed throughout the range of interest (see [20,21]). A benefit of selecting samples in this way is that convergence rates are faster, which means that less samples are needed to gain the same accuracy when compared to random sampling approaches [20].

To define the sampling, a parameter range is defined as well as the type of distribution for this variation (e.g. Gaussian, Uniform, Log-normal). In this study, we are varying 1009 parameters, and although there does exist information in the literature about typical distribution types and ranges for different classes of parameters in building energy models, it would be very time intensive to go through every parameter and assign this specific information. In light of this, a uniform distribution was chosen and a corresponding range ($\pm 20\%$) of the baseline parameter value. When the baseline value is zero, an exponential distribution is used so that more samples are adjacent to the baseline value itself. Once the samples are created, multiple models are realized for these sample values and simulated (preferably using parallel computation).

Once the simulations are complete, the data for each simulation is processed to aggregate key features of the behavior of the model for that particular DOS. Key features may include peak energy demand, annual energy consumption (broken down by end use), comfort, life cycle cost, etc. In this paper, we present results that analyze averaged predicted mean vote (PMV) of thermal comfort over all zones during occupied times, as well as annual energy consumption of the facility. PMV is an empirically developed scale

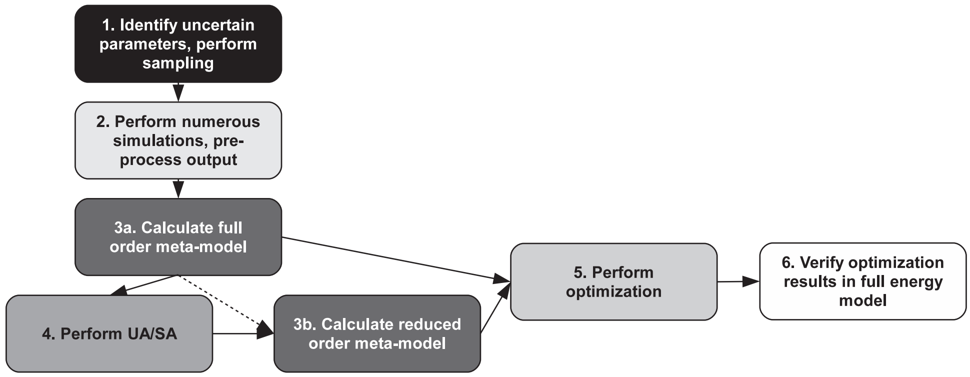

Fig. 1. Flowchart of the meta-model based optimization and analysis approach, the dotted line indicates an optional pathway. The numbering is for reference in the text.

of typical comfort levels ranging from −3.0 as cold, to +3.0 as hot with 0.0 being neutral (most comfortable) [22].

2.2. Meta-model calculation

The optimization experiments that will be performed depend on a meta-model that captures the essential characteristics of a building energy simulator while retaining a tractable functional form. The accuracy of the meta-model is important and because of this, we use a data characterization and regression technique based on statistical learning principles. Statistical (or machine) learning is a classification of algorithms that attempt to identify characteristics within data without prior knowledge of these characteristics. Machine learning has many previous applications ranging from object detection, classification of biological data, speech or image recognition, to many of the technologies related to Internet or database searching.

There are many specific approaches in machine learning (e.g. Artificial Neural Networks, Genetic Programming, Bayesian Networks), while one approach that leads itself nicely to model fitting is Support Vector Machines [23]. When implemented for function fitting or regression analysis, Support Vector Regression (SVR), provides a means to fit data using very few unknown parameters that can be found by solving an optimization problem which does not have multiple local minima. In [16] SVR was used to identify the performance of predicted energy consumption of four buildings in Singapore, and different parameters of the SVR were varied to quantify the performance of the algorithm.

The SVR approach attempts to find a function (a meta-model) whose deviation from data is at most a small constant (e.g. ε), which in turn sets up a region where errors are accepted. An optimization problem is then formulated with a parameter that trades complexity in the identified meta-model (the number of its support vectors) and tolerance to deviations greater than ε. In this way, the historical process of choosing regressors in statistical analysis is both automated and optimized. The optimization can be written as a constrained quadratic program for which many optimization approaches are available. The SVR approach is similar to learning in Artificial Neural Networks (ANN), while one significant difference is that for ANN many local optimal solutions may exist for the optimization problem, while in SVR, only one global solution exists. Along these lines, Brown et al. [18] noted that the kernel method is superior in performance to Neural Networks and utilizes parameters of physical significance.

Along with a few parameters in the SVR algorithm architecture that determine the closeness of fit, a Kernel is chosen as a basis for this fit. Many different kernels exist (e.g. linear, polynomial).

Here we use Gaussian kernel, which is the most commonly used one. In general, kernel selection depends on many things including size and characteristics of data and we will not explore all the details of this selection process in this manuscript. Further details and freely available code downloads can be found at http://www.support-vector-machines.org.

2.3. Sensitivity analysis

Given a large set of input–output sampled data from the model, uncertainty analysis (UA) can be used to identify how parameter variation influences the statistics of key outputs, while sensitivity analysis (SA) isolates which of these parameters influences output variation the most. The reason that we perform SA in the context of optimization is to identify which parameters are most influential to the optimization process. That is, it is usually useful to know which parameters influence the objective function the most so that they can be chosen as optimization variables.

To perform sensitivity analysis, we calculate total sensitivity indices (see [17,24]) for each parameter using a derivative-based approach [25]. The sensitivity index is an indicator of how influential a parameter (or combination of parameters) is on the output uncertainty. In this case, this index quantifies how sensitive an optimization result is to each parameter which facilitates many aspects of the optimization process including model reduction.

2.4. Meta-model reduction

The meta-model that is generated is dependent on numerous parameters (in this case 1009) which offer useful insight, but adds unnecessary complication in some optimization cases. For instance, it may be mathematically interesting to find the global minimum of a building DOS (for energy consumption as the cost for instance) based on all parameters, but it is unlikely that a designer will have the luxury to manipulate all of these model parameters in practice.

To alleviate this concern, a reduced form of the meta-model is created by omitting the influence of a chosen set of parameters when fitting the meta-model. There are different ways to choose which parameters to remove. One way is to remove parameters in the model that have small total sensitivity indices. In doing this, the optimization will be performed using a subset of parameters that have the most influence on optimization cost. Another obvious approach is to choose a subset of parameters that have specific physical significance to the designer (e.g. all material properties, all chiller performance properties, or all HVAC schedule parameters) even if only some of these parameters have significant influence on the optimization cost. In any case, no additional data is needed from the computationally intensive energy model. A new meta-model is simply fit to the original data with a different parametric structure.

2.5. Optimization

Optimization of the building DOS involves multiple criteria and the goal is to find a single solution that minimizes the combined criteria or objective. This well known multi-objective optimization problem has been addressed in many other building energy modeling studies. Typically there are three classes of objectives that are to be optimized; thermal comfort, operational costs, and life cycle costs. Comfort has been optimized in [1,11] and can either loosely be defined by temperature, or rigorously using a comfort index (e.g. PMV). Optimization that considers energy consumption is the most common optimization cost variable [14,12,15,26,11,9,13,27,7,28]. Energy consumption may include total facility energy use, subsystem energy use, peak demand, and seasonal or annual consumption. Life cycle cost on the other hand considers the costs of manufacturing and disposal of different components or materials in the building (typically financial, or at times environmental impact). Optimization that considers life cycle costs has been performed in [12,10,29].

In this paper, optimization is performed on many different meta-models of the original baseline energy model that began with 1009 optimization parameters. Entering life cycle data for these parameters would be very time consuming and so we limit our objective function to thermal comfort (PMV) and annual energy consumption for the facility. Since energy is used in the operation of a building to condition it and make it more comfortable, energy and comfort are naturally competitive. In Fig. 2, the probability density of comfort and energy usage is displayed from a parametric run of 5000 different building DOS iterations (the model used to create this data is described in Section 3). In the upper left subplot of this figure, DOSs which are close to the most comfortable (PMV $\cong$0.0) are selected (note that PMV within $\pm$0.5 is deemed acceptable by criterion ASHRAE-55). These same DOSs are then highlighted in the upper right hand plot showing that a comfortable DOS can consume more or less energy than the baseline DOS (the dot in the figure). Similarly, in the lower right plot, DOSs that consume a small fraction of energy are selected along with the corresponding comfort results for these same DOSs in the lower left sub-plot. Again, it is clear that a low energy building DOS can have a range of comfort, and it is the objective of the optimizer to find the best comfort for the least amount of energy.

Since we have an analytic meta-model of the building energy model, we no longer have the constraints that necessitate a DF optimization algorithm. With an analytical function, a gradient-based optimizer (e.g. an interior point (IP) method) may perform much better (in terms of accuracy and convergence time). As a means of comparison, we elect to use both methods; the DF method which is typically used in building energy research, and a gradient-based method which may use less optimization iterations.

The IP method solves linear or nonlinear convex or non-convex optimization problems by traversing the interior of a feasible region. The implementation we use is a Primal-Dual Interior Point algorithm with a filter line-search method for nonlinear programming (IPOPT) [30]. For comparison, we use the DF method (NOMAD) which contains the Mesh Adaptive Direct Search (MADS) algorithm, which is a direct search algorithm with rigorous convergence properties [31]. In each case, once the optimization is performed on meta-model, the parameters that define optimized DOS are substituted into the baseline energy model and a single simulation is performed to verify the result.

3. Case study

3.1. The building and model

As a proof of concept, we exercise the meta-model based optimization methodology on a specific EnergyPlus model of a full-scale building. The Atlantic Fleet Drill Hall (building 7230) at the Naval Station Great Lakes (Great Lakes, IL, USA) is a two-storey facility with a gymnasium-like drill deck as well as a section primarily comprised of offices. The total area of the building is approximately 6430 m^2 (69 kft^2).

The building is conditioned using four air handling units (AHUs) and has variable area volume (VAV) boxes as terminal units in the occupied zones. The gymnasium uses two AHUs, a classroom uses one AHU and the offices use the final AHU. Cooling comes from two 110-ton air cooled chillers and heating is from a district supply (which also provides the domestic hot water).

An EnergyPlus model was generated for this building (using version 4.0.0.024), and TMY3 (typical meteorological year) weather data for Chicago, O'Hare airport was used for environmental reference. To keep the size of the model manageable, 30 conditioned zones were considered (12 for the gymnasium, and 18 for the conditioned office spaces). The model takes about 15 min to simulate on a standard desktop computer with 2.8 GHz CPU (further detail about the building and its model can be found in [32]).

3.2. Sampling, simulation, and meta-modeling

In order to calculate the meta-model of the full EnergyPlus model its parameters were varied to determine how it behaves away from its baseline DOS. The parameter values in baseline model were chosen from information gathered from available as-built drawings, actual building operation (schedules), as well as some manufacturer data for the subsystems and components. EnergyPlus has many different parameters that are associated with an energy simulation including numerical solution techniques, architectural/geometry, envelope material operation, operation (e.g. scheduling of HVAC, lights, people), and mechanical/electrical equipment performance parameters (e.g. chiller rated capacity, pump efficiency). Of these, we varied all parameters in the final three (materials, operation, and equipment). When combined, there are 1009 of these parameters that were varied by $\pm$20% of the baseline. Using the quasi-Monte Carlo approach and varying all parameters at once (which is more computationally efficient), we created 5000 different DOS realizations and simulated these in parallel on a 184-core Linux cluster. This number of realizations was chosen by investigating the convergence of statistical properties of the output variables ([24] includes detailed information about the convergence analysis).

The total facility energy was calculated by adding the district hot water consumption and the facility electricity for an entire year. The PMV value was calculated for each conditioned zone during occupied hours and averaged over the zones for each time-step and then over the year to get a single representation of comfort for each parametric DOS. The SVR approach was then used to calculate the meta-model. A comparison of the raw EnergyPlus data with the meta-model prediction (for the same inputs) is presented in Fig. 3 with a comparison of the statistics in Table 1.

We note that the fit illustrated in Fig. 3 is a true model of the system and not a line fit to the distributions illustrated. That is, the meta-model is a multi-dimensional model with 1009 inputs and two outputs that produce the results in Fig. 3 when the inputs are varied in the same way as the full EnergyPlus model.

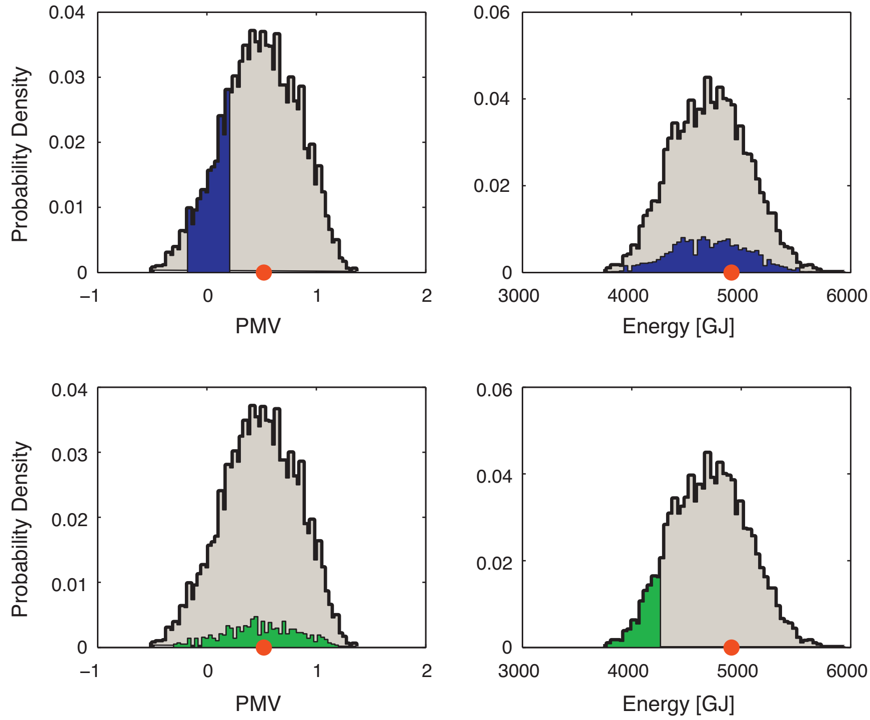

Fig. 2. Probability density of both comfort and energy usage for 5000 DOS iterations for a proposed building DOS. In the upper row, DOSs with high comfort (PMV ≅ 0) are selected, and the corresponding energy use for these DOSs is presented in the upper right. In the lower right sub-plot, DOSs with minimal energy expenditure is selected and the corresponding comfort is displayed. The dots are the values of the nominal DOS.

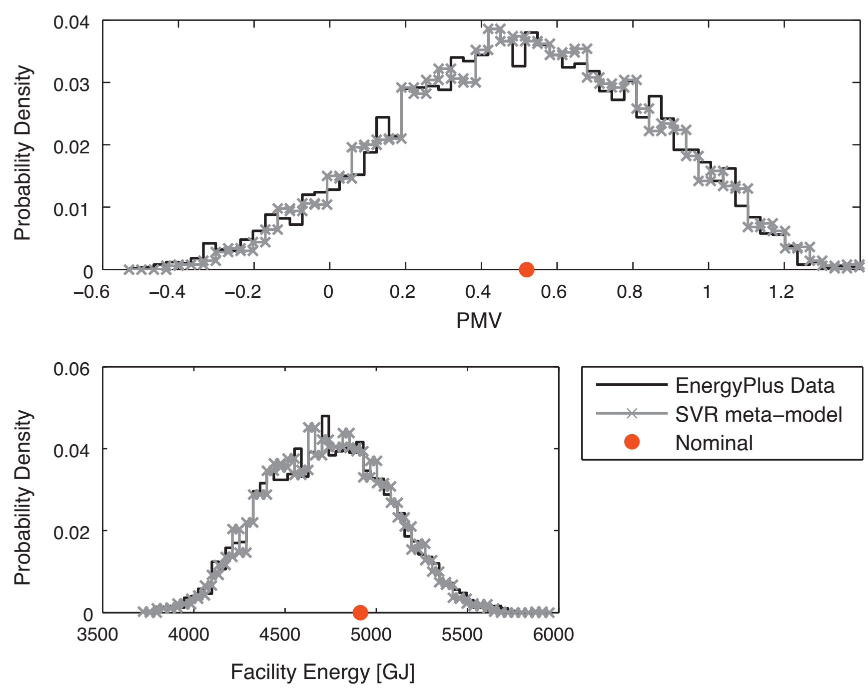

Fig. 3. Data from EnergyPlus and SVR meta-model for 5000 different DOS iterations within 20% of the baseline (nominal) DOS case.

Table 1
Comparison of the statistics of the EneryPlus simulations and meta-model calculations (using the same inputs for both cases).

	Mean PMV	Mean (energy) [GJ]	Variance PMV	Variance energy [GJ]
EnergyPlus	0.48	4713.09	0.11	115,841.48
Meta-model	0.49	4712.24	0.11	109,154.00
% Difference	2.15	−0.02	−3.41	−5.77

Table 2
Optimization results for the full meta-model with 1009 parameters. The comfort and energy calculated for the baseline and optimization cases using the three different cost functions in Eq. 1 are presented using the interior point (IP) method IPOPT and the derivative free (DF) method NOMAD. The costs are: C_1 (optimize thermal comfort only), C_2 (optimize annual energy consumption only), C_3 (optimize both C_1 and C_2).

	Baseline	IP, C_1	DF, C_1	IP, C_2	DF, C_2	IP, C_3	DF, C_3
Comfort [PMV]	0.52	0.0	−0.02	0.63	0.61	−0.09	−0.22
Energy [GJ]	4.91	4.80	5.46	2.69	2.94	2.73	2.89

3.3. Optimization

As indicated in Fig. 1 (block 5a), once a meta-model is derived for the original building energy model, optimization can be performed. This optimization was performed using a cost function that balances the influences of both comfort and energy consumption. The cost function was defined as

$$\begin{aligned} C_1 &= \mathrm{PMV}^2 \\ C_2 &= \frac{energy - min(\mathrm{energy})}{max(\mathrm{energy} - min(\mathrm{energy}))} \\ C_3 &= C_1 + C_2 \end{aligned} \tag{1}$$

where PMV was squared to drive it toward zero without taking the absolute value (continuous cost functions have better mathematical properties than discontinuous ones in this case). Since PMV is on the order of 1.0, the energy was normalized to vary between 0.0 and 1.0. The cost was broken up into two parts to identify the best possible comfort or energy solution and then a solution that balances both. The results for optimizing all parameters of the model (1009) are presented in Table 2.

For each of the optimization cases, the optimizer was executed and an optimal solution was calculated in seconds (for the interior point method) and in minutes (using the derivative free method). To ensure a proper comparison of all optimization cases, the optimal parameter choices for each case were substituted into the baseline EnergyPlus model and a single simulation was performed to calculate energy usage and average comfort over the year.

As seen in Table 2, when penalizing only comfort (using C_1), the optimization drives comfort to nearly neutral. Similarly, when penalizing only energy (using C_2), the derivative free and interior point methods reduce the energy consumption to 40% and 45% respectively. These cases show the best possible isolated comfort optimization or energy reduction while the more appropriate case of considering both (using C_3) offers energy reduction of 45% for the IP method and 41% for DF optimization. In this combinatorial case, the comfort is also optimized as well. The comfort index is reduced to −0.09 and −0.22 using the IP and DF approaches respectively.

Although some of the performance difference seen in Table 2 is expected because one method uses gradient information while the other does not, some of these differences may also be due a limitation in the number of function evaluations for the DF method (we limited the evaluations to 1,000,000, the exact number of function evaluations is presented in Table 3). Ideally, a comparison would be made between this series of optimization experiments and an equivalent set using EnergyPlus in the optimization loop instead of the meta-model. Unfortunately, the number of evaluations would be approximately 1,000,000 for this experiment with 1009 parameters, and at approximately 15 min per EnergyPlus evaluation, this test would be too computationally expensive. This highlights one of the inherent benefits of using a meta-model for optimization purposes; problems with many parameters can be handled in short time (current optimization in the buildings optimization literature studies on the order of tens of optimization parameters). We do perform a comparison of the meta-model approach with respect to traditional methods using a manageable case having 7 optimization parameters (described in Section 3.6).

Since optimization using the meta-model approach takes little computation time, we perform many other tests to identify optimal building DOSs that require optimizing fewer parameters. This highlights the second benefit of this approach; many different experiments can be performed with the meta-model without requiring exhaustive simulation. These optimization cases will be discussed in Section 3.6 after the sensitivity analysis (which drives the selection of the most influential parameters) and model reduction is discussed.

3.4. Sensitivity analysis

To guide in parameter selection for model reduction, sensitivity analysis is performed to identify which parameters offer the most leverage with respect to optimizing a certain cost. To do this, the total sensitivities are calculated as described in Section 2.3. Fig. 4 illustrates the total sensitivity indices for both PMV and total facility energy for the 1009 parameters.

As illustrated in Fig. 4, there are only on the order of 10 parameters that significantly influence either energy or comfort in this model. This suggests that an optimized solution may be achieved without necessarily changing all parameters of the building energy model.

3.5. Model reduction

Optimized performance using seven different reduced order models (including the full model discussed above) will now be considered. The first four reduced models are generated by selecting a subset of parameters based on class: (1) all schedule parameters (180 parameters), (2) all envelope material properties (142 parameters), (3) outdoor air controller properties (16 parameters), and (4) AHU fan parameters (48 parameters).

The second subset of parameters is selected based on their influence as calculated from sensitivity analysis. To identify the most influential parameters, the parameters that were presented in Fig. 4 are ordered in terms of their importance. This sorted vector of parameter sensitivity indices can be seen in Fig. 5.

Using the information in Fig. 5, three more reduced order meta-models are created that contain: (5) the top 20 most influential parameters (see Table 4), (6) the top 7 most influential parameters

Table 3
Number of function evaluations for the various optimization experiments using both the IP (IPOPT) and the DF (NOMAD) methods. Note that the function evaluations were limited to 1,000,000. Also, note that function evaluations for the meta-model take on the order of a fraction of second, while those for the EnergyPlus model take on the order of 15 min.

Optimization experiment	IPOPT	NOMAD
Full model [1009,C1]	6048	113,766
Full model [1009,C2]	23,184	1,000,000
Full model [1009,C3]	42,336	1,000,000
Top 20 [20,C3]	380	4944
Influence both PMV and energy [5,C3]	36	436
Schedule parameters [180,C3]	10,203	1,000,000
Material properties [142,C3]	35,814	854,212
Outdoor air controller [16,C3]	345	2130
Variable volume fan [48,C3]	2256	89,403
Top 7 [7,C3]	84	1312
Top 7 [7,C3] E+in the Loop	NA	726

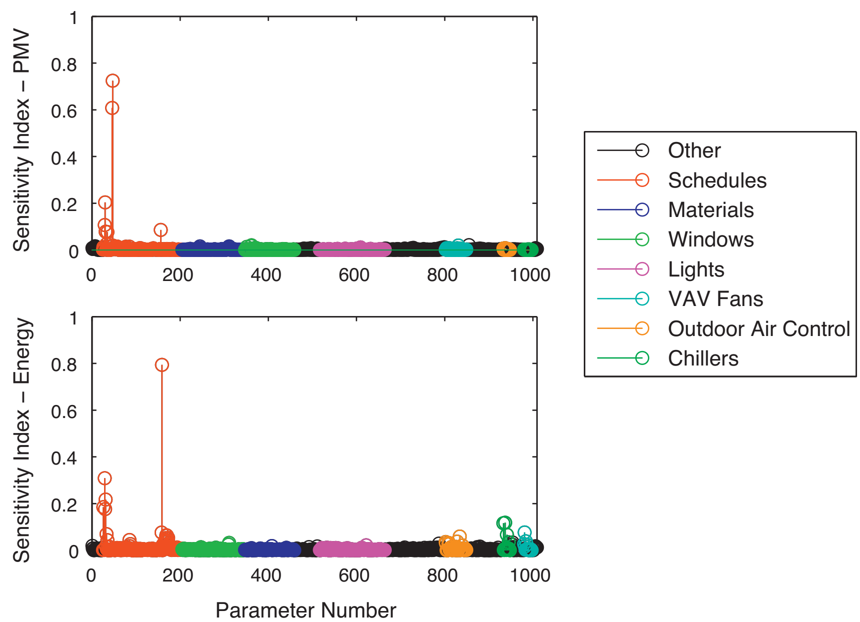

Fig. 4. Sensitivity indices for both PMV and total facility energy for the 1009 uncertain parameters. Some of the parameter classes are grouped by color in this figure. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

(labeled B in Table 4), and (7) 5 of the top 20 parameters that influence both comfort and energy simultaneously (labeled C in Table 4). This last category was selected because many of the top 20 parameters influence *only* comfort *or* energy.

3.6. Optimization

To obtain optimization results, the single full order and seven reduced order meta-models were integrated with both the IP (IPOPT) and the DF (NOMAD) optimization algorithms. Many different cost functions and weighted combinations of the cost in the three equations of 1 were investigated. For brevity we present results when using the cost function C_3 for all models, and cost functions C_1 and C_2 for the full model (with all 1009 parameters).

The results of the optimization for all these meta-models are illustrated in Figs. 6 and 7 , and compared to one case where the full EnergyPlus model was used instead of the meta-model (the data in Table 2 is also included here for comparison).

3.7. Discussion

In terms of discussing the results presented in Figs. 6 and 7, there are five topics that are worth emphasizing; the importance

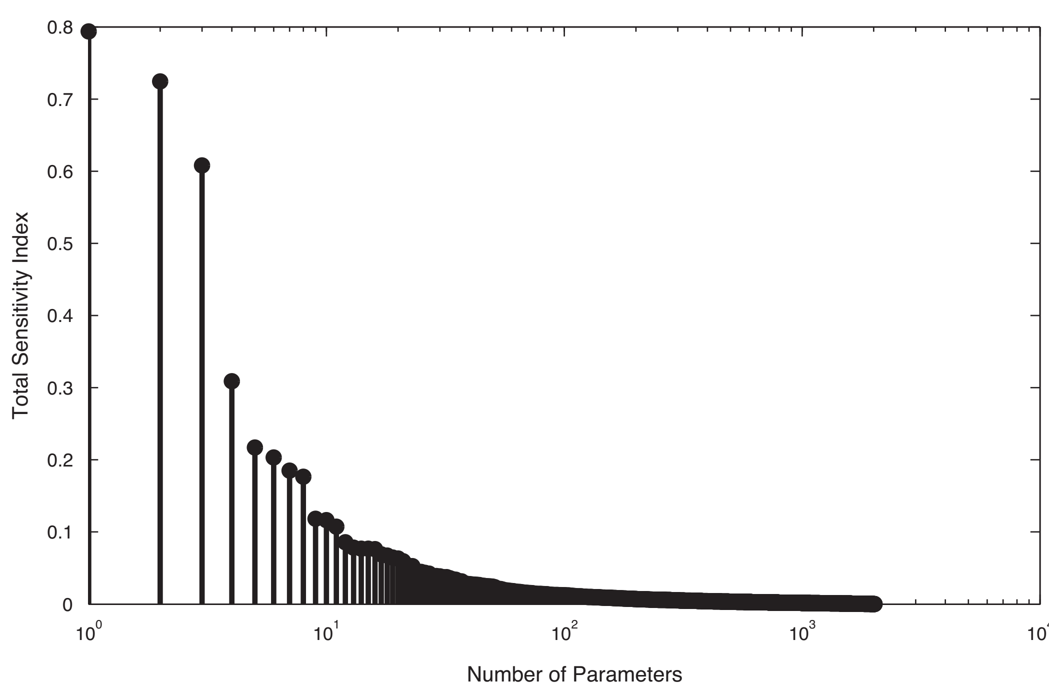

Fig. 5. Amplitude of the ordered sensitivity indices versus the number of parameters.

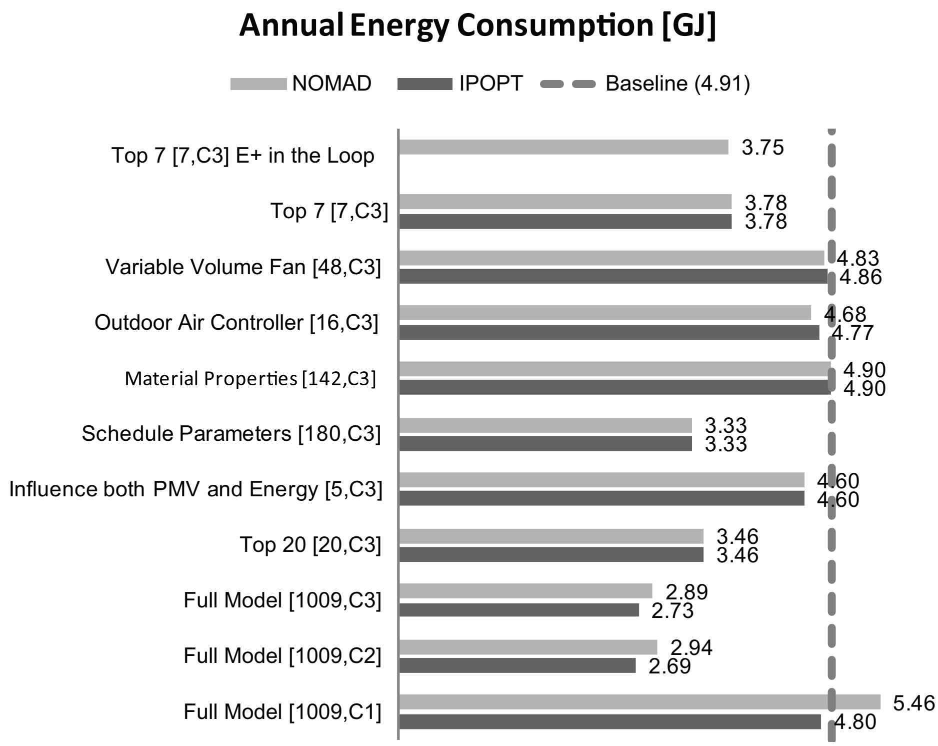

Fig. 6. Optimization results for energy consumption using the 8 meta-models, and one case using the EnergyPlus model. Each data point in this figure was generated by inserting optimal parameter values from the meta-model optimization into the full EnergyPlus model for a full simulation.

of sensitivity analysis in the optimization process, a comparison of numerical quality using a meta-model or the full EnergyPlus model, a comparison between the two optimization algorithms, a discussion on optimization seeds, and a brief discussion of computation time. These topics are itemized below.

- By comparing all of the different optimization cases which use a different number of parameters, it is evident that optimizing over even a very small subset of parameters, if chosen appropriately, will offer respectable results compared to optimizing over all parameters (by comparing *Top 7 [7,C3]*, and *Top 7 [7,C3]*

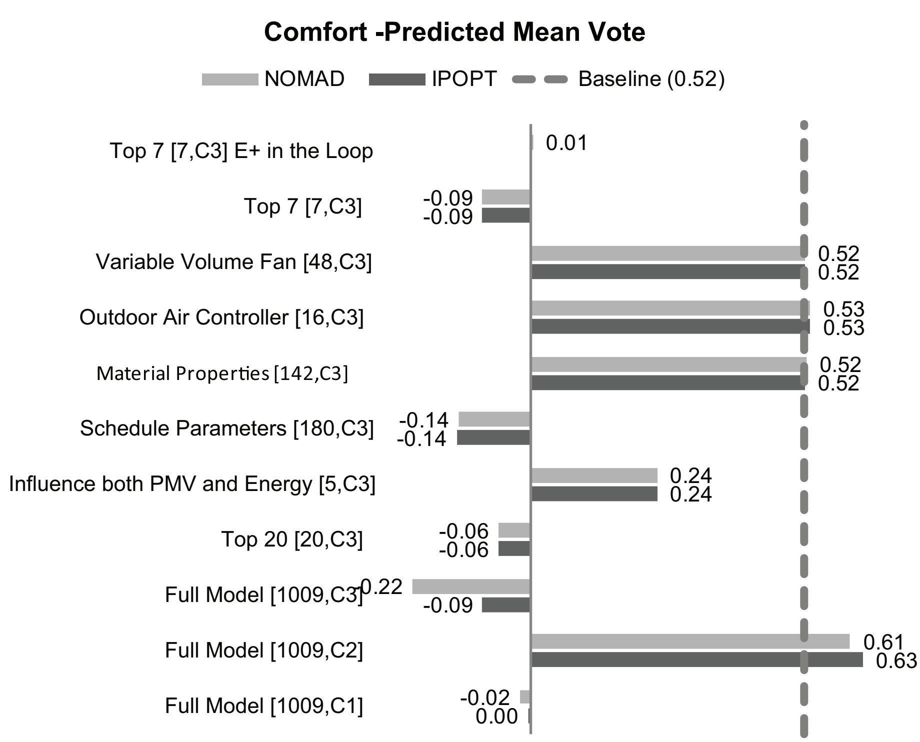

Fig. 7. Optimization results for thermal comfort using the 8 meta-models, and one case using the EnergyPlus model. Each data point in this figure was generated by inserting optimal parameter values from the meta-model optimization into the full EnergyPlus model for a full simulation.

Table 4
The twenty most influential parameters on both comfort and energy consumption.

Reduced parameter number	Label	Parameter description
1	B	Minimum outside air fraction in occupied hours
2	B,C	AHU1/2 winter (1/1 to 4/15) supply air temp. setpoint
3	B,C	AHU1/2 summer (4/16 to 8/15) supply air temp. setpoint
4	B,C	AHU1/2 winter (8/16 to 12/31) supply air temp. setpoint
5	C	Hot water supply temperature setpoint
6	C	Weekday zone temp. setpoint from 12:00 am to 6:00 am
7	B	People activity level (in W) in office area
8	B	People activity level (in W) in Drill Deck
9		AHU4 summer (4/16 to 8/15) supply air temp. setpoint
10		Domestic hot water supply temperature setpoint
11	B	Water equipment target temperature setpoint
12		Domestic hot water usage fraction from 11:00 to 12:00
13		Domestic hot water usage fraction from 12:00 to 13:00
14		Domestic hot water usage fraction from 13:00 to 14:00
15		Domestic hot water usage fraction from 16:00 to 17:00
16		AHU2 return fan maximum flow rate
17		AHU1 minimum outside flow rate
18		AHU2 minimum outside flow rate
19		AHU3 minimum outside flow rate
20		Chiller reference COP (coefficient of performance)

E+in the Loop with *Full Model [1009,C3]*). The key is performing sensitivity analysis which highlights which parameters influence the cost function the most. This notion highlights the need to integrate other analytical tools (like uncertainty and sensitivity analysis) into any optimization experiment. Rigorous parameter selection based on sensitivity analysis allows the designer to choose parameters, which may otherwise not be intuitively obvious, and rank them as to those which will have the most impact on the optimization process.

- By comparing the optimization experiments *Top 7 [7,C3]*, and *Top 7 [7,C3] E+in the Loop*, it is evident that the optimization using the meta-model offers nearly equivalent results to those obtained by performing DF optimization with EnergyPlus in the loop (in terms of numerical quality).
- In almost all cases, it is apparent that the gradient-based method IPOPT performs similarly to the derivative free method (NOMAD), with the exception when the number of function evaluations were limited to 1,000,000 (as seen in Table 3). Beyond the optimization accuracy, as illustrated in Table 3, there is a large difference in the number of function evaluations between the two methods. This is not a significant issue when using a meta-model as we have constructed (its evaluations are very rapid), but may become a concern in other situations.
- One traditional concern that has not been mentioned until now is the choice of the seed (or initial condition) for each optimization experiment. That is, both the gradient-based and the DF optimization approaches produce different (even if only slightly) results based on initial guesses of the optimization parameters. We found this variation to be so small that we do not report it for each case. For example, in the case where the optimization is performed with EnergyPlus in the loop (*Top 7 [7,C3] E+in the Loop*), four experiments were performed resulting in a variance in optimized energy of 0.00057% of mean in [GJ], and 0.28% of mean in PMV. The total number of function evaluations (15-min simulations) for these four experiments was 4688 (1172 CPU hours of simulation). Thankfully, the NOMAD algorithm is parallelized, and is run on many CPU's at once, but this series of experiments in itself (using only 7 parameters) was computationally expensive. Optimization using a gradient based-method (IPOPT) coupled to the full EnergyPlus model was not performed because expected discontinuities would have resulted in poor performance (see [7]).
- It is challenging to make a direct comparison of computational cost between the traditional optimization approach (full EnergyPlus model in the loop) and the meta-model approach because the latter offers different possibilities than the former. To be specific, one optimization experiment on the EnergyPlus model with 7 parameters (*Top 7 [7,C3] E+in the Loop*) took on average 1000 simulations. Creating the meta-model took 5000 simulations which is much larger, but once the meta-model is calculated, more optimization experiments can be performed. In other words, the meta-modeling approach becomes more computationally efficient as more optimization experiments are introduced. Given that the weighting or form of a particular cost function, or parameters of the optimization algorithm that one may be using are not always well known prior to testing (which means more than one optimization experiment is almost always needed), the meta-modeling approach becomes very attractive as a time saving measure when the entire design cycle is considered.

4. Concluding remarks

In this paper we presented an approach to perform optimization of building energy models using a meta-model generated from sample design and operation scenarios of the building around its baseline. The advantage of this approach is that once the meta-model is generated, many different cost functions, choices of parameters, or optimization algorithms can be exercised without repeating time-intensive energy simulations. The numerical quality of the solution using this approach was compared to the traditional approach using a full energy model showing good agreement and performance.

A case study was performed using an EnergyPlus model of an existing building illustrating that optimal comfort and energy minimization can be achieved using only a few appropriately selected parameters of the building design and operation scenario considered. It was found that sensitivity analysis on data generated for the meta-model provided valuable information about which parameters are best suited for optimization. Specifically, we have found that optimization of schedules (e.g. schedules for internal load profiles, outside air fraction schedules, supply air temperature setpoint schedules) has a substantial impact on both the comfort and the energy consumption in the building. This paper focuses on the optimization methodology and we leave a detailed analysis of the optimization results for future publication.

The cost function in this study was defined to minimize energy consumption while maintaining or improving comfort. A cost function can also be derived to minimize the difference between quantities calculated from the model and associated real world measurements. In this way, the methodology presented in this paper can be extended to model calibration.

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