Combined Sensitivity Ranking of Input Parameters and Model Forms of Building Energy Simulation

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Abstract

Sensitivity analysis has gradually become an intrinsic part of uncertainty analysis for the identification of key factors affecting the prediction of building performance. Traditional methods include variance-based methods, screening-based methods, and meta-model based methods. However, state-of-the art uncertainty analysis can now explicitly include hidden discrepancies in the models that we use, which typically are not characterized as exposed parameter uncertainty. These structural discrepancies have been characterized as “model form uncertainty”, similar to “model discrepancy” in the statistical realm. Another major source of uncertainty is the scenario of use that the building is subjected. In this paper, we will regard the latter as a special form of model form uncertainty. The reason for this is that scenarios (in weather and occupancy for example) are represented as time series inside the simulation and their role does not fundamentally differ from the uncertainty resulting from physical model simplifications. Then the imminent question is how to rank the sensitivity of both types of uncertainty, i.e. in input parameters and in model form. The need to do so is justified by the argument that spending effort in model improvement that turns low-fidelity modules into higher fidelity ones thus reducing model form uncertainty needs to be justified against the effect of parameter uncertainty. In other words, if the effect of parameter uncertainty is dominant over model form uncertainty, it makes more sense to concentrate on reducing parameter uncertainty. The latter may in some cases be achieved by performing additional measurements for the most sensitive parameters. Both the development of a higher fidelity model as well as conducting better parameter uncertainty quantification are costly. Any investment should therefore be driven by inspecting their relative importance which will drive the prioritization of either approach and single out the parameters or model improvements that have the highest impact on resulting uncertainty in the outcomes of the model. This paper proposes a new sensitivity analysis method that applies group lasso with discrete categorical variables and sliced Latin Hypercube sampling. By applying it on a case study building, we make several important observations, for instance, the sensitivity of infiltration ELA on heating energy consumption is highest, followed by the effect of natural weather variations as part of “scenario uncertainty”. In terms of cooling energy consumption, both weather and occupancy variability, another form of scenario uncertainty, play a dominant role.

Introduction

In 2014, residential and commercial buildings consumed about 41% of total U.S. energy consumption, or about 40 quadrillion British thermal units (EIA, 2015). Since it is recognized that energy efficiency is the least-cost energy resource option (measured by levelized cost of electricity) in the U.S. (Lovins, 2013; Molina, 2014), the focus is on designs that incorporate a drive towards (ultra) energy efficiency. It is noteworthy that buildings are complex artifacts, and as new designs push the envelope of building performance, their performance evaluation has to be backed up by comprehensive and accurate building energy predictions. For the latter, we rely mostly on building energy simulation programs.

Despite the development of current energy simulation practice, many challenges remain before the discipline reaches the level of maturity that its growing ambition in influencing design decisions demands. One of the challenges is closing the so-called “performance gap”, or minimizing the discrepancy between predicted and actual consumption. As such, the assumption that our models are adequate for guiding design evolution and planning retrofits cannot be taken for granted. Recent studies (de Wilde, 2014; Ryan & Sanquist, 2012; Turner, Frankel, & Council, 2008) emphasize this point. Specifically, Wang, Lee, Augenbroe, and Paredis (2017) point out that performance risk is one of the key barriers of the “energy efficiency” gap, which could prohibit the market from realizing the full potential of energy efficiency. Such realizations call for a closer inspection of the accuracy of our predictions, especially when these predictions inform choices between different design options. Many authors have argued that this calls for uncertainty analysis (UA) as a vehicle for analyzing how wrong our predictions can be.

Quantitative uncertainty analysis typically involves the following key components and procedures (de Rocquigny, Devictor, & Tarantola, 2008):

- A building energy computational model typically representing an idealization of the building or design of interest

- Various sources of uncertainty that render our knowledge of the value of parameters or the model imprecision
- Rationalization of decision making scenarios that motivate the uncertainty analysis

The computational model that mimics the reality can be viewed conceptually as a numerical function that links inputs (either fixed or to some degree uncertain) to outputs. Formally, if we denote the outputs as $\boldsymbol{z}$, fixed inputs as d, and uncertain inputs as $\boldsymbol{x}$, the inputs and outputs can be linked by a deterministic function $\boldsymbol{z} = G(\boldsymbol{x}, \boldsymbol{d})$. The uncertain model inputs $\boldsymbol{x}$ require rigorous uncertainty quantification (UQ) of their range and probability distribution. Some model inputs $\boldsymbol{d}$ may be fixed. For instance, they might be fully controlled without room for uncertainty, known to have negligible or secondary impact on the outcome, or they are fixed intentionally for comparative purposes. The choice of model outcomes $\boldsymbol{z}$ is driven by quantities of interest (in most cases measures that are quantified based on model outcomes) that are relevant in the decision-making process. However, once we acquire an analytical or empirical distribution for the variables of interest and performance indicator, we may need to process them to help us make decisions, as uncertainty is meaningless useless we derive a meaningful outcome in terms of a quantified measure from it. For this reason, the decision-making process typically involves so-called risk measures. A decision maker can express a risk tolerance (risk preference), usually in the form of the acceptable percentages of variability in a certain performance indicator. In this paper, we will use performance indicator as a generalized outcome typically based on time aggregation of post-processing raw model outcomes. In general, a mix of statistical measures are used to express preferences, for instance, related to expected value, confidence intervals and quantiles, and probabilities of exceeding a threshold.

Once all uncertainty distributions of the model parameters are defined, we derive the uncertainty distribution of outcomes through uncertainty propagation. Such a step is typically carried out using a Monte Carlo (MC) approach with a computationally efficient sampling technique (e.g. Latin hypercube sampling). It is well recognized that sensitivity analysis is an important added ingredient of a comprehensive UA. The concept of sensitivity analysis is encountered in various forms. It is also used to inspect one-at-a-time variations of the inputs of a deterministic model or to rank the magnitude of partial derivatives of a function. In the context of this paper, we use the term sensitivity analysis to refer to the computation of so-called sensitivity indexes for uncertainty parameters $\boldsymbol{x}$ with respect to a given performance indicator. Typical techniques include screening (Morris), regression-based methods (standardized regression coefficient), variance-based methods and so on (Saltelli, Tarantola, Campolongo, & Ratto, 2004). In the case of a variance-based sensitivity analysis, the sensitivity index represents the expected reduction in the percentage of output variance, if the parameter under investigation could be precisely known without uncertainty (i.e. having a fixed value).

Depending on the goals that motivate an uncertainty analysis, there may be feedback after the preliminary study that should be used to refine the parameter uncertainties if possible, by obtaining hering more knowledge about their possible values. If risk measures do not meet a certain criterion or the uncertainty associated with the variable of interest is too large for comparative decision making, such an iterative process may be justified, for instance to conduct measurements over certain parameters that have the largest impact on the quantity of interest with the hope that this should decrease the uncertainty range. Other options are in rare cases to shift to another decision scenario and preferences. In most cases when no better information is available, one will have to manage the outcome uncertainties as is. This could lead to over conservative designs if one wants to avoid the risks that are the result of large parameter uncertainties, especially for parameters with high level of sensitivity.

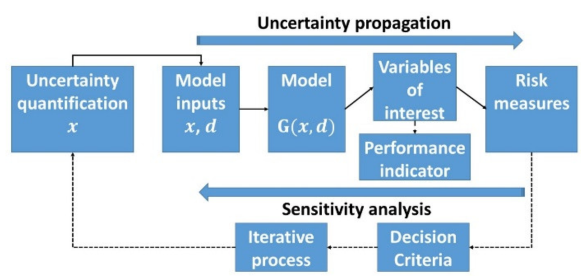

Figure 1: A comprehensive uncertainty analysis method.

Figure 1 summarizes a comprehensive uncertainty analysis method following the approach outlined above. We zoom into the sensitivity analysis approach in the remainder of this paper to exhibit its significant role in the entire method.

Literature on the topic of sensitivity analysis methods has not been scarce. de Wilde and Tian (2010) study the sensitivity of computational results to identify key design parameters, with rand regression and multivariate adaptive regression splines (MARS). Eisenhower, O'Neill, Fonoberov, and Mezic (2012) claim to extend traditional sensitivity analysis by studying the influence of about 1,000 parameters, using variance-based methods. Mara and Tarantola (2008) apply variance-based methods to a test-cell thermal model and show the hourly first-order and total sensitivity indices of the test cell's components on indoor air temperature. Mechri, Capozzoli, and Corrado (2010) also use variance-based methods to identify design variables that have the most impact on the variation of the building energy performance for a typical office building. Pappenberger, Iorgulescu, and Beven (2006) propose a global sensitivity analysis method based on multiple regression trees (random forests). Ruiz, Bertagnolio, and Lemort

(2012) also identify the most influential parameters affecting the final energy consumption in office buildings with variance-based methods. Spitz, Mora, Wurtz, and Jay (2012) apply successively local sensitivity analysis, correlation analysis, uncertainty analysis, and global sensitivity analysis to an experimental platform in France. Sun, Gu, Wu, and Augenbroe (2014) conduct parameter screening for removing insignificant parameters with lasso regression and then apply a variance-based method for computing sensitivity measures for remaining ones. Tian (2013) gives a comprehensive overview of the current state-of-the-art methods.

Literature search does not reveal a rigorous method that ranks the sensitivity of input parameters along with model forms. The need to do so is justified by the argument that spending efforts in model improvement (i.e. substitute low-fidelity modules with higher fidelity ones) and performing additional measurements for sensitive parameters can both achieve the same goal, which is to improve the precision of predictions, albeit often with quite different efforts and chance of success. To be able to study the tradeoff between both approaches, their sensitivity ranking should be combined such that their relative prioritization can be considered in one combined ranking. Furthermore, current methods only allow for the sensitivity analysis of individual parameters, but sometimes it is more relevant to see the overall sensitivity of a group of parameters. This could for instance be relevant for all parameters that jointly influence the prediction of convective heat transfer coefficients. Therefore, we choose to apply group lasso with discrete categorical variables and sliced Latin Hypercube sampling as the basis of our sensitivity analysis method (Ba, Myers, & Brenneman, 2015; Yuan & Lin, 2006). Discrete categorical variables are introduced to deal with the different model form uncertainties, each of them denoted by a specific model variable that can either take the value 1 (present) or 0 (not present). The categorical variable thereby indicates the influence of model form uncertainty. For each model form, a separate categorical variable is introduced. Another use of categorical variables will be introduced later.

Method

The method that we propose applies the proven method of group lasso with discrete categorical variables and sliced Latin Hypercube sampling. We first establish a link between the proposed method and traditional ones.

Recap of Variance-Based Methods

Since variance-based methods are the most popular methods for sensitivity analysis, we first recap some background information from Saltelli et al. (2004). The widely-accepted variance-based methods yield robust and accurate global sensitivity measures without relying on any assumption on the nature of the input to output relations.

Assume that all the uncertainty parameters X are free to vary over the entire range of uncertainty, then the overall uncertainty of the outcome of interest $y = f(X)$ is measured by its unconditional variance $V(Y)$. The goal of a sensitivity analysis is often to rank the uncertainty parameters according to the amount of output variance that is removed when we learn the true value of a given input parameter X_i. Parameters could then be ranked with $V(Y|X_i = x_i^*)$, the variance obtained by fixing X_i to its true value x_i^*. Note that the $V(.)$ operator above is taken over all other parameters but X_i. We can normalize the measure by the unconditional variance $V(Y)$, which leads to $\frac{V(Y|X_i=x_i^*)}{V(Y)}$. However, we soon come to the realization that the true value x_i^* of X_i is unknown, so it is natural to compute an average value of the above measure over all possible values of X_i. The parameter with the smallest $E(V(Y|X_i))$ should be ranked as the most influential to the outcome. In a rich notation, $E_{X_i}(V_{X_{-i}}(Y|X_i))$ denotes that the mean of the conditional variance, where X_{-i} stands for the vector of input parameters but X_i. Given that $V(Y)$ is a constant, and can be decomposed into $V(E(Y|X_i))$ and $V(E(Y|X_i))$ (law of total variance), searching for the smallest $E(V(Y|X_i))$ is equivalent to maximizing $V_{X_i}(E_{X_{-i}}(Y|X_i))$, which is the variance between the conditional means. As such, we define two sensitivity indexes as follows:

- First-order effect: $S_{X_i} = \frac{V(E(Y|X_i))}{V(Y)}$, where $V(E(Y|X_i))$ is expected reduction in the output variance that one would get if X_i could be known or fixed, or top marginal variance.
- Total effect: $ST_{X_i} = \frac{E(V(Y|X_{-i})}{V(Y)}$, where $E(V(Y|X_{-i})$ is the expected residual output variance that would end up with if all factors but X_i could be known or fixed, or bottom marginal variance.

Features of First Order Effects

S_{X_i} is a good model-free sensitivity measure as it always gives the expected reduction in the variance of the output if one could fix an individual parameter. A nice property of these is that the sum of $S_X s$ is one, if the model is additive. A model $Y = f(X_1, X_2, \ldots, X_k)$ is additive if the function f can be decomposed as a sum of k functions, and each f_i is the function of only one individual parameter X_i. Note that the definition above suggests an additive model is free from parameter interactions.

Connection with Standardized Regression Coefficients

It turns out that under certain circumstances, one can find a one-to-one correspondence between S_{X_i} and the squared standardized regression coefficients, as mentioned by Mara and Tarantola (2008). To be more concise, for linear models with independent inputs, $S_{X_i} = \beta_{X_i}^2$. For instance, assume a linear model $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \epsilon$, where input parameters are normalized to have mean 0 and standard deviation 1. It is easy to show that

$S_{X_1} = \frac{V_{X_1}(E_{X_{-1}}(Y|X_1))}{V(Y)} = \frac{V(\beta_0+\beta_1 x_1+E(\beta_2 x_2+\epsilon))}{V(Y)} = \frac{\beta_1^2}{\beta_1^2+\beta_2^2} = \beta_1^2$. (1)

This result indicates that if our building energy model is linear with regard to input parameters (this is usually the case if we are dealing with aggregated eneryg outcomes), we can compute the first-order effect sensitivity index in variance-based methods with linear regressions.

Group Lasso with Discrete Categorical Variables and Sliced Latin Hypercube Sampling

Sensitivity analysis in our specific context desires several specialized features: it should enable a fair comparison between continuous variables (input parameters) and discrete categorical variables (indicators of different model forms), and be able to consider the combined sensitivity of several uncertain parameters as a whole. We explain as follows a method that meets such requirements.

As already explained, we introduce categorical variables to include model forms in our SA. For instance, in the case of HVAC uncertainty, the value of the respective categorical variable 0 denotes the model form that ignores HVAC uncertainty, while 1 indicates otherwise. Another use of categorical variables is for handling weather: if we have 41 years of historical weather data for Atlanta, then the categorical variable for weather will have 41 distinct levels, which can be translated to 40 dummy variables for regression purposes. The translation of multi-level categorical variables to dummy variables is explained in any statistical texts about regression.

The sensitivity index of the categorical variable indicates the importance of considering one type of model form uncertainty relative to other input parameters. However, the interpretation of the standardized regression coefficients should be altered to accommodate categorical variables, as the notation of mean and variance makes little sense for them. To overcome this, we choose to use

$$\frac{SSR-SSR_{-X_i}}{SSR}$$

to measure the sensitivity of all parameters, discrete or continuous. In the equation above, SSR is the regression sum of squares for including all significant parameters from the group lasso, while SSR_{-X_i} denotes the regression sum of squares for leaving out parameter X_i from the pool. Therefore, the metric intuitively measures the reduced amount of variation explained by the regression model for leaving X_i out. For continuous independent parameters,

$$SSR = SSR_{-X_i} + \beta_i^2 V(X_i),$$

so the measure is equivalent to previous notations in (1), but is now able to accommodate categorical variables.

Grouping of Variables with Group Lasso

Lasso (least absolute shrinkage and selection operator) is a regression method that conducts both variable selection and regularization, introduced by Tibshirani (1996). In its basic form, lasso's objective is to minimize (with regard to β)

$$\frac{1}{N}\|y - \boldsymbol{X}\,\beta\|_2^2 \text{ subject to } \|\beta\|_1 \le t,$$

where $\|Z\|_p = (\sum_{i=1}^{N} |Z_i^p|)^{1/p}$ is the standard l^p norm. In addition, t is a tuning parameter, which determines the level of shrinkage. Let $\widehat{\beta^o}$ be the full least squares estimates and let $t_0 = \sum |\widehat{\beta^o}|$. If $t < t_0$, lasso will shrink all coefficients towards 0 by a similar amount, and sufficiently small coefficients are shrunken to exactly 0 (James, Witten, Hastie, & Tibshirani, 2013). Therefore, insignificant parameters are eliminated in the screening step.

Yuan and Lin (2006) propose group lasso as an augmentation to the basic version. Group lasso allows predefined groups of parameters to be selected in or out of the model together. The most natural use of group lasso is that it can either include or exclude all levels of a categorical variable altogether, as it makes no sense to select only a few levels of a categorical variable. Suppose there are J groups of parameters, the group lasso estimation minimizes

$$\left\|y - \sum_{j=1}^{J} X_j\beta_j\right\|_2^2 + \lambda \sum_{j=1}^{J}\left\|\beta_j\right\|_{K_j},$$

where $\|z\|_{K_j} = (z^t K_j z)^{1/2}$, K_j is a positive definite matrix, and λ is a tuning parameter. In the formulation of group lasso, the design matrix X_j and coefficients β_j for each group of parameters replace the design matrix X and coefficients β in the old notation.

Sliced Latin Hypercube Sampling

We assume the common knowledge that basic Latin Hypercube sampling is a more efficient design than the traditional brute force Monte Carlo, for exploring the design space uniformly. However, now we are faced with the situation of sampling with the presence of categorical variables. If we use the traditional Latin Hypercube sampling, the design will not guarantee that at each level of the categorical variable, the remaining parameters fill the design space efficiently, which may give certain level of the categorical variable underserved advantage in the sensitivity analysis to come. Therefore, we advocate the application of the optimal sliced Latin hypercube sampling (SLHS) (Ba et al., 2015) as an extension to the traditional LHS. An SLHS has the following features: (1) for the m samples under each level of the categorical variable, all marginal distributions on continuous variables are stratified into m strata with equal probability; (2) for all the $N = m \times t$ samples combined (t is the number of levels for the categorical variable), the marginal distributions on continuous variables are stratified into N strata with equal probability; (3) the samples achieve the maximum uniformity and space-filling property.

Case Study

Sensitivity Analysis Description

In this section, we conduct a sensitivity analysis with the proposed method on the medium office building from the DOE reference building pool (Deru et al., 2011). The building has three floors, and each consists of a core zone and four perimeter zones. The system in the building includes a central packaged air conditioning unit with a gas furnace for heating and cooling, and variable air volume (VAV) terminal boxes with reheat for air distribution. In the sensitivity analysis, we study quantities of interest such as whole-building energy consumption in Atlanta. Input parameter uncertainties are drawn from the UQ repository described in Section 3.2 by Wang (2016), and we consider the following categorical variables summarized in Table 1.

Table 1 Categorical variables considered in the study

Categorical Variables
Historical Weather
Wind speed, wind pressure, infiltration
VAV systems
Occupancy, lighting/appliance usage

The first categorical variable deals with uncertainty associated with weather, as future weather is unknown at the design stage. We take 40 years of historical weather data in Atlanta to represent the variability of future weather conditions. For the second, we group wind speed, wind pressure and infiltration model forms together, as they represent microclimate conditions around the building and they combine to affect the calculation of the amount of infiltration into the building. These model forms are detailed by Sun, Heo, et al. (2014) for wind speed and wind pressure, and by Wang (2016) for the infiltration model. The third one is rated to HVAC systems. We implement quantified uncertainty with the EnergyPlus representation of VAV systems described in Wang (2016). The last one is detailed in Wang, Augenbroe, Kim, and Gu (2016), which improves the prediction fidelity of occupancy and lighting/appliance usage by a stochastic model. By turning on or off each of these model form uncertainties, we essentially derive $2^4 = 16$ distinct combinations of model forms.

In the sensitivity analysis, we first generate 16×500 samples with SLHS. Then, we combine the uncertainty analysis results at each level for the overall uncertainty distribution of the outcome of interest. In our implementation of group lasso, we use the well-established R package grplasso (Meier, 2015), with prescribed grouping indexes from our physical knowledge. For instance, all parameters on material properties are grouped as one, while those influencing the interior convective heat transfer coefficient are grouped as another one. In total, we divide 161 parameters into 12 groups, i.e., ground reflectance, internal heat transfer coefficient, exterior heat transfer coefficient, ground temperature, wall materials, window materials, duct pressure loss, weather, wind pressure/speed, VAV model form, occupancy and lighting/appliance. These groups are included or excluded altogether by lasso selection and regularization. Finally, sensitivity ranking of remaining significant parameters are ranked with the measure $\frac{SSR - SSR_{-x_i}}{SSR}$.

Results and Discussions

We show the results of the sensitivity analysis on both heating and cooling energy for the case study building located in Atlanta, in Figure 2.

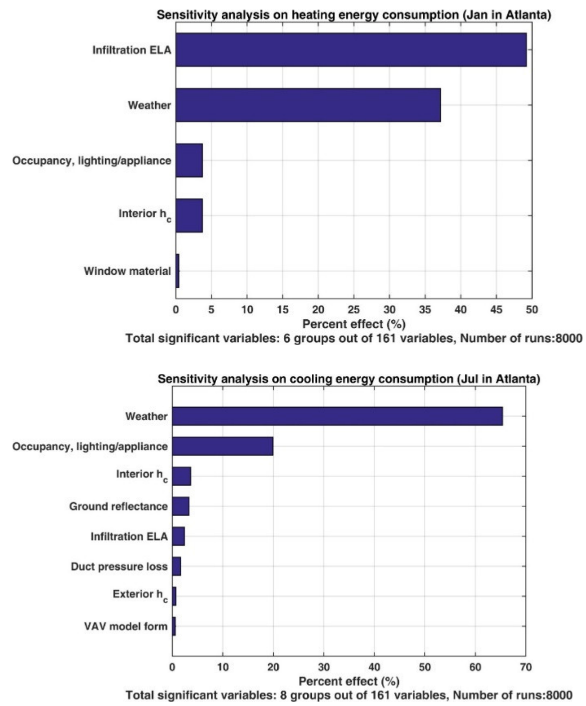

Figure 2 Sensitivity index for heating (upper) and cooling (lower) consumption in Atlanta

In Figure 2, both parameter and model form uncertainties are ranked together. For instance, the sensitivity of infiltration ELA on heating energy consumption is high, followed by the effect of considering historical weather as a "scenario uncertainty". In terms of cooling energy consumption, weather and occupancy variables, as scenario uncertainties, play a dominant role. A deeper examination of the impact of occupancy, lighting/appliance shows that for aggregated energy consumption prediction in an office building, more efforts should be focused on the estimation of the mean profiles of lighting/appliance usage, i.e. direct electricity use linked to occupancy. We know from previous studies that knowledge of occupancy presence is less important for the building-mediated heating and cooling energy outcomes (Wang et al., 2016). Another interesting finding is that the quantified uncertainty of local wind speed, wind pressure and the infiltration model show negligible sensitivity on both heating and cooling energy consumption. This should be interpreted with care as the major uncertainty in the amount of infiltration is apparently the result of the uncertainty in the façade leakage parameter ELA.

It should be noted that the combination of parameter and scenario uncertainty is not always the most sensible approach. Indeed, if the historical weather contains outliers, it is to be expected that the weather, considered here as a scenario uncertainty will end high in the ranking. But it is very dependent on the decision-making context whether anybody is really interested in this. In most cases, the decision maker will be more focused on making the right decision for the average or even a normative year. In such a case, the weather is fixed and plays no role in the sensitivity ranking. In another situation, the decision maker may be interested in the expected energy consumption over many years and specifically what effects drive the yearly variation relatively the most. The focus of our approach is on a method that is adequate to perform the analysis in both cases.

Iterative Uncertainty Analysis

We have to recognize that a generic uncertainty analysis, i.e. for a building for which the design is available but a lot of specific location and construction specific data is not available usually makes little sense as our uncertainty distributions will be large and the outcome distribution is by necessity also very large. Such a generic UA is at best useful as a first iteration step. It is to be expected that a specific decision related to a performance measure is hardly well served by such a first iteration. A second iteration will require a more specific uncertainty quantification that updates the initial or generic guess with additional knowledge augmented by specific (collected) data. To illustrate this in our example, we re-examine the uncertainty of the façade leakage parameter ELA. This is one of our targets for the second iteration as the sensitivity analysis results show that ELA ranks highest on the influential factors for heating energy. Currently, we rely on previous research (Wang, 2016) and characterize the distribution of ELA as $lognormal(1.282, 0.879^2)$, when no specialized information on the building of interest is available. However, to manage uncertainty and risk for decision-making, we assume a blower door test is performed on similar nearby buildings with the same façade technologies from the same company. We assume that this new knowledge greatly reduces the uncertainty of ELA. From the measurements, the ELA is estimated to be following the distribution of $normal(2, 0.1^2)$. Therefore, we are able to conduct a second-iteration of the uncertainty analysis (in general accompanied by a sensitivity analysis), which enhances our confidence in the energy outcomes and therefore offers more reliability to conduct the ensuing decision-making scenarios.

Figure 3 shows the comparison between predicted heating energy consumption with and without specialized information, considering all uncertainties besides weather. Note that the uncertainty range has been reduced significantly. The resulting model may infuse more confidence into certain decisions such as the need for operational intervention or fault detection.

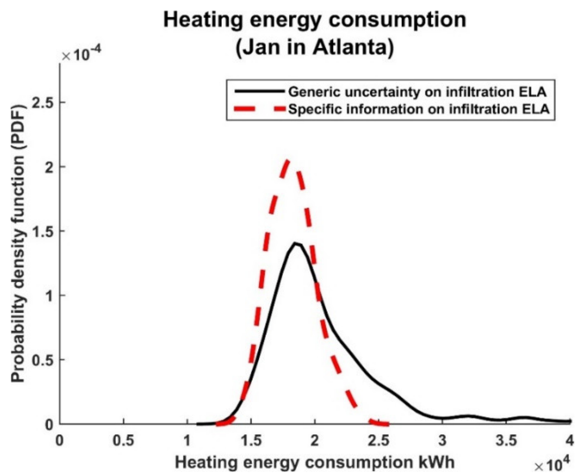

Figure 3 Results of original and refined uncertainty analysis

Conclusions

The method development and its test on a case study lead to the following conclusions:

(1) The sensitivity analysis method that we propose augments and supports a new-generation uncertainty analysis, in terms of the combined ranking of input parameters with model forms.

(2) For cooling energy consumption, the sensitivity of infiltration is high, followed by the effect of considering historical weather as a "scenario uncertainty". For cooling energy consumption, weather and occupancy variables, both scenario uncertainties, play a dominant role.

Finally, GURA-W (Georgia Tech Uncertainty and Risk Analysis Workbench) (Lee, Sun, Augenbroe, & Paredis, 2013) offers an efficient platform that automates the process of performing the sensitivity analysis. Once familiar with the process, the model development requires a level of effort that is comparable to current practice.

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