Building Energy Performance Estimation in Early Design Decisions:
Quantification of Uncertainty and Assessment of Confidence

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ABSTRACT

Building energy assessment models support design decisions, which should only be made if stakeholders are confident that the decision taken will result in a preferred outcome. Despite this fundamental notion, the assessment of confidence in decisions is not included in current energy assessment tools. Uncertainties in model inputs and in the appropriateness of the models used leads to uncertainty in model outputs and therefore to a reduction of confidence in the decisions supported by those outputs. In early design stages there is great uncertainty about how a design might evolve, which leads to large uncertainties in predicted outcomes, rendering the appropriateness of performance prediction to the decision questionable at this phase unless these uncertainties are quantified and used in performance predictions. Here we propose a quantification of these uncertainties and preliminarily examine their impact on confidence in design decisions using a case study.

INTRODUCTION

One of the uses of mathematical, physics-based building energy models is the prediction of future performance in support of technical design decisions. However the future cannot be known with certainty due to uncertainties in the inputs to the model as well as models' fundamental nature as imperfect abstractions of reality. These uncertainties lead to uncertainties in the outputs, which when quantified using probability theory and incorporated into decision-making, allows stakeholders to make choices with an estimate of the risk associated with that choice - or seen another way, the confidence in that choice.

In typical use, the set of inputs - i.e. the set of independent variables - is composed of a subset of scenario variables which includes initial/boundary conditions like weather and occupancy; and a subset of design specification variables, also called parameters or design parameters, which encode the design of the building as viewed by the mathematical model. These physics-based models are inherently deterministic, and their typical use is likewise deterministic. A value for each of the independent variables is specified, the model is run, and a value is computed for each of the dependent variables. This implies that the independent variables are known with certainty, which is not the case in general.

For scenario variables, neither the weather nor the use of the building in the future is known with certainty, although these may be estimated within bounds. Here we denote these uncertainties scenario uncertainties. Similarly the design parameters are not known with certainty. For the parameters it is often helpful to distinguish between two types of uncertainty which together constitute design parameter
uncertainty. The first type encodes a lack of knowledge about the values of the parameters which have been decided upon, that is, those parameters that reflect an aspect of the building whose design is complete. A wall's geometry and construction may have been specified and materials selected, however the properties associated with those materials, e.g. thermal conductivity, is not known with certainty because the actual values can differ from reported values due to manufacturing defects, improper installation, etc. The certainty that the choice was made does not mean certainty in the value of the model parameters associated with that choice. We call this decided parameter uncertainty.

The second type of design parameter uncertainty is undecided parameter uncertainty, which encodes a lack of knowledge about values of parameters which have not been specified. This type is relevant only in design phases. If the model and its results are being used to inform design decisions, not all of the design parameters have been decided upon. Indeed the model may be being used to help decide on some of those very parameters, while a decision on other parameters may be deferred until later. At the start of design none - or few - of the parameters have been decided upon and both decided and undecided parameter uncertainty is present; at the end of design, all the parameters have been decided upon and only decided parameter uncertainty is present. If we wish to make decisions at some time in the design process in the presence of undecided parameters, we need to account for the fact that we do not know what decisions we will make in the future. In other words, how the design will develop is itself an unknown. The impact on the expected performance outcome of a design decision made at an early time may be influenced by subsequent design decisions made at later times.

For design decisions to be made in an early phase, undecided parameter uncertainty poses a significant challenge to making well-informed performance-based choices. Although many ‘simplified’ or reduced-order tools have been developed to address the needs of early building design decisions, for example the MIT Design Advisor tool of (Urban, 2007), to our knowledge none incorporate decision making under undecided parameter uncertainty. This study focuses on such early decisions under this design uncertainty.

Although a physics-based model is deterministic by nature, we can use it in a non-deterministic way, by replacing point values for the independent variables with histograms or probability distributions on the independent variables. These distributions quantify the uncertainties in these variables, and are propagated through the model using techniques such as Monte-Carlo sampling. The resulting histograms on the dependent variables are interpreted as probability distributions representing the uncertainty in the performance outcome. Examples of such uncertainty propagation in the building performance domain are given in (de Wit, 2001), (Sanguinetti, Eastman, & Augenbroe, 2009) and (Hopfe & Hensen, 2011).

In order to make a decision among different options under uncertainty, a decision-maker needs to be confident in the outcome of that decision. One may be fully confident in a decision if the probability distribution on the performance outcome of one option favorably dominates the other probability distributions with respect to time in the design process. In the absence of a dominating effect, the notion of confidence in a decision must account for the decision-maker's attitude
toward risk; that is, there is a probabilistic degree of confidence in a decision which is fully subjective to the decision maker. In this work we include this notion of a degree of confidence, but consider as out-of-scope the precise elicitation of a decision-maker's attitude toward risk. In short, we propose that to make an early design decision, the question to ask is not “is this option better than that option?”, but “are we confident that this option will be better than that option”?

Numerical uncertainty arises in the computational procedures and machinery used to calculate a model's dependent variables, and while important, we assume such uncertainties are small compared to those in the independent variables. Uncertainty is also embedded in a model itself: every model is an imperfect representation of reality or imagined future reality and thus cannot represent reality in totality or with perfect accuracy and precision. In the case of mathematical models this imperfection comes from the choice of variables used to quantify reality and the equations that form the relations between those variables. There are many possible mathematical models that may be used to represent the physics of reality, with some being more faithful, or simply more useful, than others. This sort of uncertainty is called model uncertainty and is implicitly touched on in this study, along with undecided parameter uncertainty.

The nature of this implicit consideration of model uncertainty is tied to the notion of a valid, or merely adequate, model. We use the definition of a valid model as given by (Hazelrigg, 2010) as a starting point:

“A model is valid if, when used in a specific decision making situation with a given set of available alternatives and the decision maker's beliefs and preferences, the decision maker is certain that his preferred choice is the choice that indeed yields the outcome that is most preferred from among the outcomes that could have been obtained from the set of available alternatives.”

By this definition, model validity is wedded to decision-maker confidence, and a model is valid only if it supplies complete and total confidence in a decision. All other models are invalid. Furthermore, all valid models are equivalent from a decision standpoint, regardless of the sophistication of the models. Complete confidence or complete lack of confidence are not the only possibilities. There may be degrees of confidence, and there may be degrees of model validity, or adequacy, based on degrees of confidence in a decision supported by that model.

We conclude this introduction by stating our present research objectives: to determine if, and if so what, architectural design decisions can be made in early design with confidence that the outcomes will be the preferred outcome, and also to investigate the influence of different models on this confidence.

METHODS

Consider the set of design parameters $P = \{p_1, p_2, p_3, ..., p_m\}$ of a mathematical model. At any point during the design process, this set can be divided into two subsets $P = \{P_{\text{dec}}, P_{\text{undec}}\}$ where $P_{\text{dec}}$ contains the parameters that have been decided upon, and $P_{\text{undec}}$ holds parameters that have not been decided upon. Before design commences, all parameters in $P$ are in $P_{\text{undec}}$ and $P_{\text{dec}}$ is empty. At the completion of design the situation is reversed, with $P_{\text{undec}}$ being empty and $P = P_{\text{dec}}$. During design both $P_{\text{undec}}$ and $P_{\text{dec}}$ are non-empty, with $P_{\text{undec}} = P \setminus P_{\text{dec}}$. 
How $P$, which is particular to each energy model, is partitioned into $P_{\text{dec}}$ and $P_{\text{undec}}$ is determined at least partly by a given decision situation. Here we consider a decision situation to consist of a design decision to be made together with the available alternatives and the setting of that decision. More specifically, a decision situation has:

1. The building (and its type, etc.) and its site.
2. Stakeholder preferences, including the associated performance indicators.
3. The set $P = \{p_1, p_2, p_3, \ldots, p_m\} = P = \{P_{\text{dec}}, P_{\text{undec}}\}$.
4. A subset $P_{\text{todec}} \subseteq P_{\text{undec}}$ whose elements $\{p_{\text{todec,1}}, p_{\text{todec,2}}, \ldots, p_{\text{todec,n}}\}$ that are to be decided upon. Note that at the final design decision, $P_{\text{todec}} \subset P_{\text{undec}}$.
5. The available design options, a.k.a. alternatives $= \{a_1, a_2, \ldots, a_k\}$. Each alternative $a_i$ will set the values, or probability distributions, of all elements of $P_{\text{todec}}$.
6. The set of outcomes $O$ whose elements correspond to the options in $A$: $O = \{o_1, o_2, \ldots, o_k\}$, determined using an energy model. These outcomes are measured using the performance indicators from item # 2 above. Under uncertainty, each outcome $o_i$ is described with a histogram or probability distribution.

The decision is to use the energy model to estimate the outcomes in $O$ from the alternatives in $A$, then, based on stakeholder preferences, select the alternative that results in the most preferred outcome -- or more completely, is the alternative in which we are sufficiently confident will result in the most preferred outcome. When this is done, all the elements of $P_{\text{todec}}$ are transferred from $P_{\text{undec}}$ to $P_{\text{dec}}$.

Relating to item # 2 above, for this work we only consider preferences on heating and cooling demands, under the assumption that decisions regarding HVAC systems will be made later in the design process, as well as to simplify the scope of this initial study. The performance indicators for the outcomes $O$ are thus the yearly thermal cooling and heating loads, i.e. $o_i = Q_{\text{yc}}^{a_i}$ and $Q_{\text{yH}}^{a_i}$ respectively, and stakeholders will prefer these to be low in all cases. Additional work regarding actual delivered energy is possible, but this involves HVAC system type and use, with another set of associated uncertainties. Given our focus on early design decisions, we limit the scope to decisions on the building and consider HVAC system decisions to be considered at a later stage.

Assessing confidence in early decisions and the influence of models

A decision-maker's confidence in a decision is partially a function of their attitude toward risk. If, under uncertainty, the outcome probability distributions of two alternatives do not overlap, then the choice of the more preferred option can be chosen with complete confidence. However if these distributions do overlap, then the amount of overlap and the attitude toward risk influence the confidence in a decision as supported by a particular energy model, and this confidence will generally not be complete. The metric we propose to quantify this confidence, with outcomes $o_i$ estimated using a given energy model, $M_j$, is the probability that relative differences
Δρ between two outcomes meets or exceeds a subjective threshold. We denote this PRD for probability of a relative difference, defined in the following equation for yearly cooling loads. For notational compactness we substitute alternatives \(a_1, a_2\) etc. with alternatives \(a_1, a_2\), etc.

\[
PRD_{yC,M_j} = Pr[\Delta_{r,yC}(a_1, a_2, M_j) \geq \Phi] = Pr\left[\frac{Q_{yC, M_j}^{a_1} - Q_{yC, M_j}^{a_2}}{Q_{yC, M_j}^{a_1}} \geq \Phi\right]
\]

and similar for heating loads \(Q_{yH}\). Here \(Q_{yC, M_j}^{a_1}\) is a normalizing yearly cooling load and \(Pr[...]\) denotes the probability of what is in the brackets, determined from histograms computed from the propagation of uncertainties in \(P_{\text{unc}}\) through model \(M_j\). The variable \(\Phi\) is a decision-maker preference on the relative difference between alternatives \(a_1\) and \(a_2\).

Because there is a chance that the relative difference between outcomes may not meet or exceed that threshold, a decision-maker would need to express a preference on the chance that one alternative is indeed \(\Phi\) better than another, as determined by a given model. We denoting this preference on this chance as \(\Psi\) so that in effect, if one wishes to be confident, at level \(\Psi\), that the outcomes estimated by model \(M_j\) will be \(\Phi\) different at the end of the design process, then one can choose between these outcomes if

\[
PRD_{yC,M_j} \geq \Psi
\]

Two models are used in this study. One, EnergyPlus (Crawley, Lawrie, Winkelmann, & Pedersen, 2001) and (DOE, 2013), is an established dynamic building energy simulation program. The other is a simple, normative, quasi-static building energy model based on the ISO 13970 standard (ISO, 2008). Although this normative model was developed as a calculation procedure in support of the normative rating of building designs, we use it here as a reduced-order model in contrast to the more complex model of EnergyPlus and to investigate the use of simple models during early design under uncertainty in design evolution. Previous studies have shown this normative model not only to produce ratings comparable to ratings derived from detailed simulation, but also to be useful for purposes beyond rating and to yield results comparable to established building energy simulation programs at substantially lower cost in modeling and computation, see, e.g. (S. H. Lee, Zhao, & Augenbroe, 2011) and (Kim, Augenbroe, & Suh, 2013).

**Quantification of design parameter uncertainty**

For this work we consider that the only source of uncertainty is undecided parameter uncertainty. In this conception the energy model is purely deterministic at the end of design, even though this is not realistic since scenario, decided parameter, model, and numerical uncertainties will be nonzero. However we assume that these types of uncertainties are not significant to the questions this research seeks to answer: because we are asking about confidence in decisions in early design where uncertainty in how the design may evolve is large, only the confidence in the (ordinal) rank-ordering of the alternatives is the decision criterion. In such
comparisons the question is not “how much better is \( a_1 \) than \( a_2 \) ?” but “are we confident that design \( a_1 \) will be better than \( a_2 \) once the design specification is complete?” The uncertainties other than undecided parameter uncertainty are common to all design options and are thus assumed to contribute no actionable information to the decision. While cardinal utilities are certainly important to any design process, we consider these to be out of scope for the present work and only consider decisions to be based on ordinal comparisons.

Therefore, the parameters in \( P_{\text{dec}} \) are considered to be certain and each element of \( P_{\text{dec}} \) is quantified with a single real number rather than being quantified with a probability distribution. In contrast the parameters in \( P_{\text{undec}} \) are considered uncertain and each element of \( P_{\text{undec}} \) is quantified with a probability distribution encoding undecided parameter uncertainty.

Given an energy model and its set of parameters \( P \), no further work can be done until distributions for \( P_{\text{undec}} \) encoding undecided parameter uncertainty have been determined for \( P_{\text{undec}} \). Computing these distributions is the keystone task of this work; indeed these distributions will constitute an important contribution in themselves, in addition to answers to the research questions.

The method to determine these distributions is described in detail in chapter 3 of (Zhao, 2012) but here a conceptual overview is given. Typically, a model is executed in ‘forward’ fashion, from independent variables quantifying the scenario and design to dependent variables quantifying performance. In contrast, an ‘inverse’ execution uses empirical data for the values of the (formerly) dependent variables, using it as input to the model, or a surrogate model of this original model, in order to calculate as output the values of the (formerly) independent variables. With uncertainty, the empirical data for the (formerly) dependent variables are expressed as histogram data, in this case drawn from the CBECS 2003 dataset (EIA, 2006) for the building type and climate of the decision situation. The inverse calculation is done on a linear statistical model derived from the normative model, using established linear inverse problem techniques. The resulting histograms are thus estimates describing the population of the design parameters for buildings of the specified type and climate. Here we additionally interpret these histograms as estimates of probability distributions quantifying the undecided parameter uncertainty.

Two issues should be noted. First, these histograms likely incorporate some decided parameter uncertainty. Second, the histograms are taken to be independent of one another, that is, there is no information regarding the probability distribution of one parameter given a value of another parameter. It is possible that this independence is not realistic, however we defer such considerations for later work.

The distributions representing the uncertainties in the undecided parameters \( P_{\text{undec}} \) were found to approximate uniform distributions. These uniform distributions were then used in the computation of \( PRD \) with both the normative model and EnergyPlus, with the EnergyPlus representation of the building defined to correspond to that of the normative model.

When a decision is to be made, the parameters that pertain to that decision make up the set \( P_{\text{todec}} \), and the values of these parameters are at this decision point considered to be deterministic, taking on the values appropriate to each alternative.
Likewise the parameters in $P_{\text{dec}}$ are considered deterministic, while the remaining parameters in $P_{\text{undec}}$ are considered uncertain. The forward mode of model execution is then used, with uncertainties propagated by Monte-Carlo sampling techniques, yielding model outputs in the form of histograms. From these histograms the metric $PRD$ is computed.

**CASE STUDY**

Although our research focuses on early design decisions, one of our case studies is a deep renovation of an existing building. The Caddell building (figure 1) on the Georgia Tech campus is a relatively small, two-story office building in the initial stages of being renovated. This renovation is expected to involve the removal of the facade and all interior elements and building systems, essentially taking the building down to the structural skeleton. Here we consider this state to be a surrogate for an early design stage, with a few building parameters such as building form, size, and orientation already decided, with the majority of the parameters yet to be decided upon.

Figure 1. Caddell Building

The design decisions involve choosing the ratio of fenestration area to opaque wall area of the facade and the type of shading devices. Specifically, two alternatives have been proposed by the design team:

Alternative $a_1$: The whole east side of the building receives a new transparent facade, with the rest of the building's facade remaining opaque. The roof outer surface will be highly reflective and feature a large overhang for shading the eastern facade, sized to prevent direct sunlight in hottest time of the year.

Alternative $a_2$: The whole east as well as one third of the north and south sides of the building receives a new transparent facade while the rest of the building's facade remains opaque. Fins are used instead of the overhang for shading.

With these two alternatives, the set $P_{\text{undec}}$ is give in table 1. The choice is essentially to choose values of those parameters in $P_{\text{undec}}$ under consideration in alternatives $a_1$ and $a_2$, i.e. choose values of the parameters in $P_{\text{todec}}$, and move them to $P_{\text{dec}}$. With these two alternatives we are choosing values of the window to wall ratio and the shading device factor, so $P_{\text{todec}} = \{P_{14}, P_{21}\}$. Note that $P_{15}$ and wall area $P_{18}$ are adjusted as needed to maintain consistency. Uncertainty propagation is conducted using the ModelCenter (PHX, 2013) middleware; the normative model is
implemented in a spreadsheet making ModelCenter integration simple, whereas a plugin developed at Georgia Tech (B. Lee, Paredis, & Augenbroe, 2013) is used to integrate EnergyPlus in ModelCenter.

Table 1. The set $P_{\text{undec}}$

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Parameter</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>$P_{11}$</td>
<td>Roof U-value</td>
<td>$P_{17}$</td>
<td>Window transmittance</td>
</tr>
<tr>
<td>$P_{12}$</td>
<td>Roof absorption coefficient</td>
<td>$P_{18}$</td>
<td>Wall area</td>
</tr>
<tr>
<td>$P_{13}$</td>
<td>Roof Emissivity</td>
<td>$P_{19}$</td>
<td>Wall U-value</td>
</tr>
<tr>
<td>$P_{14}$</td>
<td>Window to wall ratio</td>
<td>$P_{20}$</td>
<td>Wall transmittance</td>
</tr>
<tr>
<td>$P_{15}$</td>
<td>Window area</td>
<td>$P_{21}$</td>
<td>Shading device factor</td>
</tr>
<tr>
<td>$P_{16}$</td>
<td>Window U-value</td>
<td>$P_{22}$</td>
<td>Shading correction factor</td>
</tr>
</tbody>
</table>

Results and discussion

The results of propagating the uncertainties through both models are depicted in figure 2. Note that these histograms should not be interpreted as the uncertainty in the thermal loads of the finished building because the building is not only unbuilt, it is not even fully designed yet. Rather these histograms represent an estimate of the uncertainty in loads due to the multitude of options available to the designers from this moment in the design process but not yet chosen.

Figure 2. Histograms of cooling and heating loads under uncertainty in $P_{\text{undec}}$; x-axis units are kW/m$^2$

Histograms for heating loads for the two alternatives show much overlap within (both) models, although there is a difference in the absolute numbers between the normative model and EnergyPlus. Both models show a slight difference in
expected value of heating loads, but a decision-maker could not choose the lower expected value with much confidence. This lack of confidence is related to the overlap in the histograms, and not to the small difference in expected values.

In the case of cooling loads, there are again differences in the values of the outcomes between models, as well as in the compactness of the histograms. However, both models show a clearer distinction between alternatives, with each model output suggesting alternative $a_1$ (solid line) to be preferred to $a_2$ (dashed line), although by different margins since the overlap between outcomes is greater for the normative model than EnergyPlus. Both models suggest the same decision, but at different levels of confidence.

Table 2 quantifies these qualitative arguments. Taking $\Phi = 0.1$ as the preference on relative difference between outcomes and $\Psi = 0.75$ as the preferred probability that that relative difference is met or exceeded, it is seen that only EnergyPlus suggests that a decision - namely choosing alternative $a_1$ - can be made under the stated preferences on relative difference and confidence, but only for cooling loads. Furthermore, choosing an alternative on the basis of heating loads using any of these two models, or cooling loads using the normative model, is not a decision that can be made at this point in the design process given the preferences encoded in $\Phi$ and $\Psi$.

<table>
<thead>
<tr>
<th>Table 1. Probability of relative difference; $\Phi = 0.1$ and $\Psi=0.75$</th>
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<tbody>
<tr>
<td><strong>Normative model</strong></td>
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<tr>
<td><strong>Heating</strong></td>
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<tr>
<td>PRD, $\Phi = 0.1$</td>
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<tr>
<td>Confidence at $\Psi = 0.75$</td>
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CONCLUSION AND FUTURE WORK

This research focuses on the most problematic aspect of implementing energy analysis at the earlier stages of design: the assessment of confidence in decisions is not included in current energy analysis tools, and applying them at the early stage of design that poses high level of uncertainties, particularly regarding design evolution, is not appropriate. In this study, we have considered these design evolution uncertainties in early design and their impact on confidence in design decisions regarding building performance. For the case study used and the stated preferences, both models either show a near equivalence between alternatives or suggest the same choice of alternatives. However only EnergyPlus' estimates showed enough spread between one particular set of outcomes to suggest that a decision can be made with the stated preferences on the probability of a relative (or percent) difference. This implies a certain confidence in a decision, however we believe this confidence in a decision cannot be definitively assessed until confidence in a model is definitively assessed, given that two models imply different confidence. Rather we interpret these results as one model encouraging a choice now while another implies the deferral of that choice until a later time.
Two other case studies are being conducted in complement to this one. Furthermore all case studies are being examined under a variety of preferences on Φ and Ψ.

We note in closing that the technique used here for representing these design uncertainties has the useful property that it does not require that all choices be combinatorially enumerated. However whether or not this technique covers all possibilities in the design space is left unanswered. Relatedly, the assumption of the independence of the histograms for parameters in \( P_{undec} \) needs to be examined.

REFERENCES


Zhao, F. (2012). Agent-based modeling of commercial buildings stocks for energy policy and demand response analysis. (Doctor of Philosophy), Georgia Institute of Technology.