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THE EFFECT OF MODELER DECISIONS ON SIMULATION UNCERTAINTY: SOME IMPLICATIONS FOR USER INTERFACE DESIGN

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ABSTRACT

Previous research has shown that building energy simulation (BES) users introduce uncertainty to the simulation process. Analogous research in the area of computer security provides a framework for identifying BES user interface (UI) features that may be modified to reduce differences in simulation results caused by modelers. An original data set from participant energy modelers is expanded through Monte Carlo sampling and then analyzed with random forests. The Monte Carlo data is compared to the factor analysis data from a previous paper to uncover basic classes of impact for modeler decision categories. The results indicate that UI features that require complicated input methods (e.g. HVAC and lighting power entry) or that demand specific estimates of unknowns at the time of modeling (e.g. plug loads and schedule) are the most significant sources of output differences. Designs for BES UI features are provided that are expected to significantly reduce uncertainty introduced by the modeler. For cases where the suggested changes to the UI are non-trivial, a methodology for defining changes is proposed. These UI designs will both rely on and inform future Uncertainty Quantification (UQ) research in BES.

INTRODUCTION

Unaddressed uncertainty in BES inhibits the credibility and the usefulness of results at a time when there is a growing need to rely on simulations to manage risk in the design of buildings, particularly high performance buildings. In recognition of this need to incorporate uncertainty analysis (UA) into the simulation process, recent research has sought to characterize uncertainty in weather (Lee et al., 2012), building materials (Macdonald, 2002; Struck and Hensen, 2006), and microclimate variables (Sun et al., 2013), among other model parameters. Further research has been conducted in methods of incorporating uncertainty analysis into the modeling process (Lee et al., 2013) and in applications of UA for the design of offgrid houses (Hu, 2009), energy retrofits (de Wilde et al., 2002), and investment decision-making (Bozorgi and Jones, 2010).

However, in the absence of comprehensive information on the role the modeler plays in converting building plans or conditions into an energy model, UA research is limited in its ability to capture the true uncertainty associated with BES. Previous research has investigated the sensitivity of the model of a residential building to possible user decisions (Bloomfield, 1986). Other research has experimentally explored the difference in energy predictions that different modelers make for a given set of plans (Guyon, 1997; Ibarra and Reinhart, 2009; Bradley et al., 2004; Berkeley et al., 2014) . Despite the differing conditions of these studies, including various combinations of novice and professional modelers and commercial and residential buildings, all found considerable differences between the predictions made by different modelers.

Although it is impractical or impossible to reduce the uncertainty in most components of BES, such as weather, construction, building materials, or building use conditions, it is possible to reduce the uncertainty caused by modelers through appropriate BES UI design. Research is currently lacking on the mitigation of modeler-based uncertainty through BES UI design, but research into computer security measures provides an analogy. Just as it would be ideal for simulation outcomes to be free of the influence of individual modelers, researchers in computer security have found that having no “humans in the loop” is the optimal way to maintain security. However, both fields have practical limitations on the ability to remove humans from the decision-making process. In BES, changes at every stage from design through the end use of the building demand a human interpretetation of building features and conditions. Likewise, in computer security, humans are sometimes necessary to enforce or interpret measures that are not feasible for computers to follow through on (Cranor, 2008).

With the inability to remove humans from the loop in computer security, the question became: What can be improved in the security process to reduce security breaches caused by users? (Cranor, 2008) lays out a method of applying the human in the loop security framework to security systems. The steps are listed below with explanations adapted to their BES applications in order to answer the question: What can be improved about BES UIs to reduce the impact modelers have on simulation results?

1. Task identification: determine which features of building simulation are affected by modelers.
2. Task automation: automate modeler inputs wherever possible, to whatever extent is possible.
3. Failure identification: for the tasks that cannot be

automated, figure out how modelers could introduce uncertainty or error.

4. Failure mitigation: develop methods of reducing likelihood of failure during modeler interaction. In (Cranor, 2008) this step is primarily achieved through communication (i.e. warnings, notices, status indicators, training, and policies).

The following sections of this paper through "Discussion of Modeler Decisions", in combination with (Berkeley et al., 2014), contribute to the first step. The section "UI Design Recommendations" will cover the second, third, and fourth steps above (although the third step is implicit). Research into security systems that attempt to reduce human error, such as the work of Maxion and Reeder (2005) on file permissions interfaces, shows promise for the reduction of modeler uncertainty through the design principles laid out in this paper.

MODELER STUDY

The research presented in this paper builds on the work presented in (Berkeley et al., 2014), where professional energy modelers were placed under conditions that replicated those experienced during a typical modeling project.

Experimental procedure and results

Professional energy modelers were found through local professional society email list serves. The twelve who participated were provided identical plans to a moderately complex school administration building (Figure 1) that would be reasonable yet challenging for participants to fully model in the allotted time (three hours). The building was situated in the climate zone that all participants were accustomed to modeling within, and all participants had experience with the modeling program (eQUEST) and modeling commercial buildings.

Participants were provided with the architectural plans, as well as the lighting plans and schedules and the mechanical plans and schedules. Four packaged single zone (PSZ) HVAC units were included in the mechanical plans, as well as 2 split system HVAC units and 4 exhaust fans. Plans indicated the location of a domestic water heater, but no equipment information was included. Lighting plans indicated both interior and exterior lights.

All participants completed a simulation of the building within the required time. Results for total yearly electrical consumption varied by -11% to $+104\%$ and results for gas consumption varied by -61% to $+1535\%$ when compared to a baseline model. A comparison of simulation predictions with modeler demographic background data yielded no apparent bias in energy predictions from modeler experience. A more detailed investigation into modeler decisions was therefore warranted.

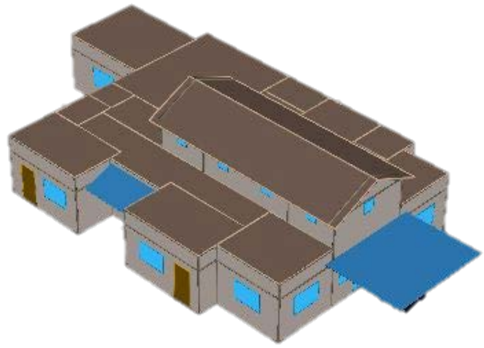

Figure 1: School administration building modeled by participants

Previously reported analysis of study results

A best-practices model was created with high fidelity to building plans to serve as the baseline model for a factor analysis of participant modeling decisions. Participant decisions for the HVAC system caused the greatest deviation from baseline predictions for electricity, while equipment power decisions (i.e. plug loads) caused the greatest variation between modelers. Nearly all deviation and variation from the baseline model in gas use was explained by participant HVAC decisions. Because the analysis isolated one factor at a time, the effect of interactions between various modeler decisions was not uncovered. In order to explore how modeler decisions would impact simulation results in a larger population, a Monte Carlo analysis was performed.

MONTE CARLO ANALYSIS

Method

Parameters for the Monte Carlo analysis were set up to be those outlined in Table 1. Figure 2 demonstrates the sampling method, whereby 200 complete models were created from randomly selected inputs for each parameter. The distributions for the Monte Carlo sampling were taken to be the distribution of the inputs from the participant data in order to simulate the results that would be expected from the entire population of the modeling community (if they were to all model this same building and make individual decisions with the same frequency as the study participant sample). The input file for the single story baseline model used for the factor analysis served as the reference model for the Monte Carlo-sampled data. Participant decisions replaced each block of the reference model code except the floor plan geometry, which had to be kept consistent for reference by variables included in the substituted blocks of code.

Table 1: Monte Carlo factors with corresponding reference names. Note that the HVAC factor is broad due to an inability to define granular HVAC parameters that would be universally interchangeable between HVAC systems.

Ref. Name	Factor
SiteData	Site data
EWall	Exterior wall properties
IWall	Interior wall properties
ExtLtg	Exterior lighting power
DHWeqp	Domestic water heater properties
DHWloop	DHW loop
ZoneType	Zone type
PeopleSch	Occupancy schedule
LgtSch	Lighting schedule
EqpSch	Equipment schedule
InfSch	Infiltration schedule
InfFlowArea	Infiltration rate
PeopleHGLat	LHG (people)
LtgWArea	Lighting power
EqpWArea	Equipment power
Occupancy	Number of people
Geometry	Space and plenum height
Windows	Windows
HVAC	HVAC (equipment and zoning)

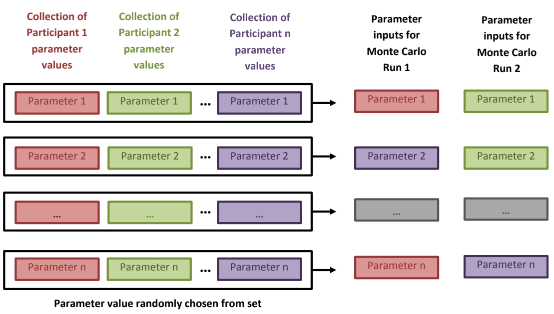

Figure 2: Demonstration of Monte Carlo sampling method for investigating interaction and frequency effects in study data. Parameters for the Monte Carlo analysis are the same as the factors denoted in Table 1.

Results

The results of the Monte Carlo analysis are included in Figure 3. Results for electricity usage indicate that the interactions between participant decisions yield a roughly normal distribution, and that the baseline model fell just within a standard deviation of the average of the Monte Carlo models (although the baseline results were not within a standard deviation of the participant data). Gas data did not have a normal distribution, however - results were muiltimodal, with peaks centering around key HVAC decisions. In order to better understand which decisions had the strongest interaction effects, random forests were employed (as discussed in the following section).

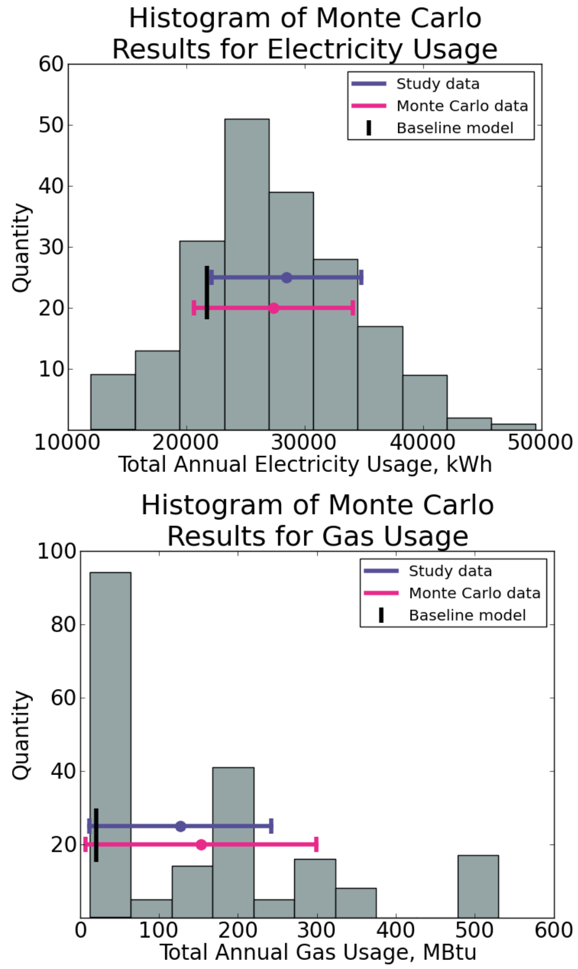

Figure 3: Plot of Monte Carlo simulation results for total annual electricity use (top) and total annual gas use (bottom). The distribution of energy predictions from this analysis is what could be expected if all modelers in the population (not only the modelers in the study sample) modeled the building used in the study. Mean values and one standard deviation are displayed for participant data and Monte Carlo results.

RANDOM FOREST ANALYSIS

While the Monte Carlo method increased the effective sample size from twelve to 200 for the purposes of this analysis, the number of relevant parameters (nineteen) is still large in comparison to the sample size. Random forests are useful for determining which input parameters are responsible for the greatest interaction effects when there are relatively large amounts of parameters compared to the sample size (Tian, 2013). The random forest method ranks parameter importance through a bootstrapped sampling of classification trees; one "vote" is given to a parameter every time it surfaces as the most important parameter in any given classification tree. The relative parameter importance can be determined by comparing the total number of votes received by parameters within an analysis. R's FactoMineR package was used to carry out the random forest analysis on the Monte Carlo data (Lê et al., 2008). Separate analyses were carried out for total yearly electricity predictions and for total yearly gas use.

Random forest results

Figures 4 and 5 display the importance of a given parameter in determining the outcome of the simulation. The exact quantity of votes are arbitrary and determined by the particular random forest algorithm, but the relative importance of the parameters is not arbitrary and is characteristic of the input data.

These rankings are reflective of the modeler decisions in combination with the sensitivity of the model to the given parameter. If modelers made, for example, identical decisions about how to represent the HVAC system, the random forest method would not find the HVAC system parameter to be particularly successful at predicting simulation outcomes, despite the model's high sensitivity to this particular input category. Furthermore, the random forest results uncover parameters that are successful at predicting the simulation outcome when a more significant parameter is fixed between models. This last feature of random forest results will be particularly useful in framing the discussion of modeler decisions below.

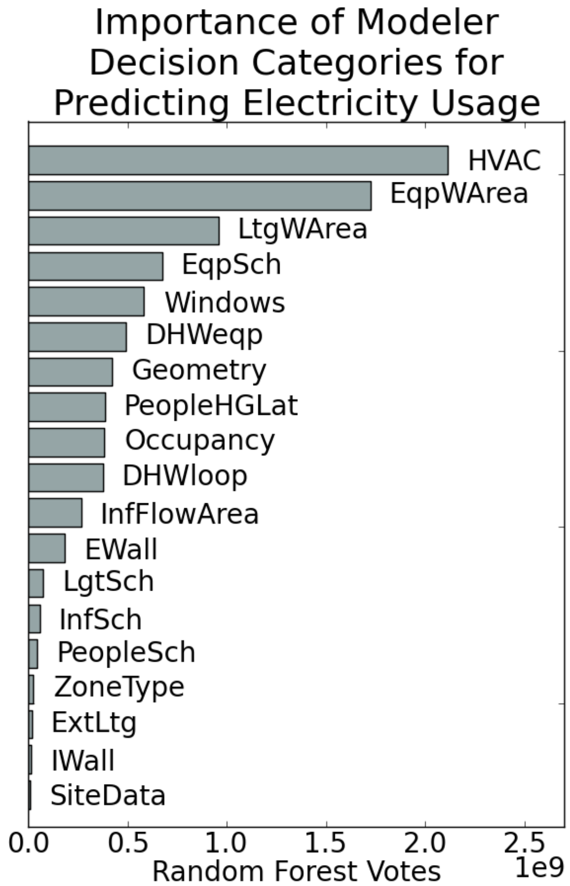

Figure 4: Random forest results for total annual electricity use. Votes (on the x-axis) represent the number of times a given parameter was successful at differentiating simulation results. See Table 1 for full descriptions of reference names.

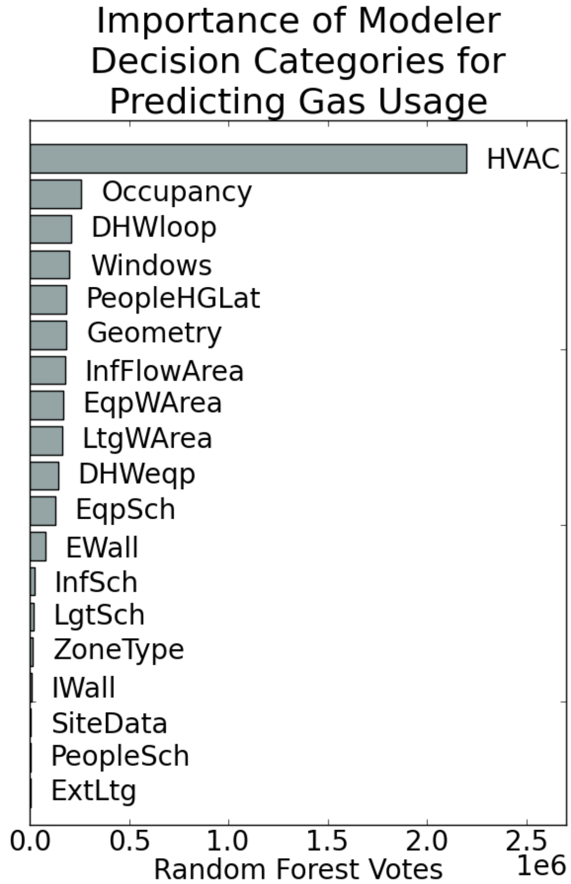

Figure 5: Random forest results for total annual gas use. Votes (on the x-axis) represent the number of times a given parameter was successful at differentiating simulation results. See Table 1 for full descriptions of reference names.

DISCUSSION OF MODELER DECISIONS

A discussion of modeler decisions hinges on the basic features of the analytical methods used. In the previous paper (Berkeley et al., 2014), the factor analysis provided:

- Understanding of single categories of modeler decisions because of how they relate to the baseline model results
- A measure of uncertainty in modeler decisions (i.e. the standard deviation in simulation outcomes for a given modeler decision category).

In this paper, the random forest analysis yields:

- Ranking of the importance of specific modeler decisions when in a population of modelers (i.e. when compared to a model other than a consistent baseline).
- Decisions that are only significant in the presence of other specific model conditions.

Types of modeler decisions

There are three basic classes of modeler decisions that naturally develop from comparing the one-at-a-time factor analysis (OAT) and random forest analyses:

1. High OAT impact, low random forest impact
2. Low OAT impact, high random forest impact
3. High OAT and random forest impact

In the discussion that follows, modeler input decisions will be clustered in the same fashion as the parameters explored in the Monte Carlo analysis (see Table 1 for the comprehensive list of input groupings; only the most significant ones will be discussed here, however).

Input groups that fall into Class 1 will be ones where modelers consistently differ from the baseline model, therefore producing high OAT impact, but where they do not have a large effect on Monte Carlo-sampled (i.e. population level) simulation results, thereby producing a low random forest impact.

Input groups included in Class 2 are ones that did not produce a large difference in combination with the particular input values of the baseline model, but that surface as significant when combined with the input values decided on by the modelers in the study.

Class 3 covers the most significant category of input groups: those that cause results to deviate from the baseline model (and with a high degree of uncertainty) and that are important even in combination with all other participant input values.

Table 2 summarizes the inputs that belong in each class described above and for this particular experimental setup. While different populations of modelers and different building plan and climate zone information could potentially cause specific input groups to shift categories, the framework for determining input classes will be broadly useful for identifying the potential impact of improvements to BES UI design for each of these classes. For the purpose of providing concrete examples in the discussion of UI design that follows, the input group classifications from this particular study will be maintained throughout.

Table 2: Classification of the most significant decision categories in modeler study.

Class	Description	Examples
1	high OAT, low random forest	Exterior lighting, lighting schedules, domestic water heater equipment
2	low OAT, high random forest	Space and plenum heights, windows
3	high OAT, high random forest	HVAC equipment, lighting power, Equipment power, equipment schedule

UI DESIGN RECOMMENDATIONS

The modeler decision classes described in the previous section serve as indications of which UI design changes would be most successful at reducing modeler uncertainty, and under what conditions. In this section, UI design changes will be recommended following the methodology laid out by Cranor (2008). Namely, this section addresses which modeling tasks can be automated, and how to mitigate potential modeler uncertainty in the tasks that cannot be automated. Many of the recommended UI design features will be helpful for ameliorating uncertainty derived from various classes of modeler decisions, so notes will be made at the conclusion of each subsection on the predicted impact of the feature on modeler uncertainty.

Simplify input methods where possible

Information on lighting power and HVAC equipment typically are provided to modelers in high detail. While this high level of detail could lead to a high level of fidelity for the building model, in current practice highly detailed plans are too time intensive to be fully represented in the model. Additionally, entering detailed plans often provides many opportunities for typographical or unit errors to be made. HVAC equipment is the single largest source of discrepancy between modelers for both electricity and gas usage predictions, due in part to modelers running out of time to faithfully input all HVAC equipment features. Fully detailed HVAC equipment could be made available in a BES program through the Building Component Library (BCL) first proposed in (Fleming et al., 2012). The emerging ASHRAE Standard 205 is expected to address this problem by providing a standard format for manufacturers to provide equipment performance data for use in simulation (ASHRAE, 2015). While not as significant as HVAC data entry, lighting power entry would also be improved by BCL-style component selection.

This UI design feature would be the easiest to implement but also would potentially contribute to the greatest reduction in modeler uncertainty out of all the recommendations, since it addresses two input groups from Class 3.

Encourage choice of standard uncertainty profiles for inputs unknown at the time of modeling

Lee et al. (2013) already established the methodology for implementing uncertainty in models corresponding to known parameter values. A common source of modeler uncertainty, however, is the need for a modeler to choose an input value from a recommended range when the specific value is unknown at the time of modeling, thus leading to an arbitrarily pinned value within the range of expected values. An example from the research presented in this paper comes from equipment power decisions: all modelers chose equipment power values within the range recommended by the ASHRAE Fundamentals Handbook (ASHRAE, 2013), yet equipment power led to the largest uncertainty in modeler results. In addition to equipment power, actual building use schedules (occupancy, lighting, and equipment) are rarely known to modelers. Standardized power densities and schedules are required for energy code compliance and rating scheme submissions. For cases where the intent is to predict actual performance, it should be possible to associate user-defined or standardized uncertainty profiles with user-defined power densities and schedules.

This UI design change will be simple to implement according to the procedures established by Lee et al. (2013) and will reduce uncertainty caused by Class 3 and Class 1 modeler decisions.

Communicate certain functions of simulation program to modelers more clearly

Modelers typically receive training in the simulation program they use (Berkeley, 2013) and have access to the user manual. However, users commonly forget detailed knowledge of the system they are interacting with (Maxion and Reeder, 2005), e.g. what window information is required by a certain simulation tool for calculating thermal performance vs. daylighting performance. Rather than expecting users to remember these details or resort to help manuals, desired user behavior can be encouraged with appropriate and proactive communication of this knowledge through notifications and warnings (Maxion and Reeder, 2005; Cranor, 2008).

In an example scenario, a BES program may allow modelers to precisely locate windows along a wall in the event they are performing a daylighting simulation. However, if a modeler is only performing a thermal analysis of the building, the precise location of the windows will not be required because the program will only use total window area in heat transfer calculations. To encourage modelers to accurately represent the relevant data for the task, a notification window could pop up when the modeler enters a detailed window entry mode, notifying them that precise window location will only be used in daylighting simulations; otherwise, only total area is relevant.

The specific features that require notification are largely simulation-program dependent, but are likely to include the coupling of spaces, thermal mass, zone definitions, and any other feature where the data entry process is deceptively different from how the model algorithms handle the data. Although the specific input groups that will benefit from this implementation are the most likely to be different between simulation programs, they are very likely to manifest as Class 2 inputs. (For example, one program may allow the user to enter potentially unnecessary data for windows, while it disallows extraneous information for thermal mass; another program may permit the opposite scenario. In both programs, however, the situations where potentially extraneous information is allowed are likely to become Class 2 inputs - when the program does not use the information it will have minimal effect on simulation results, but when it does use this information it will have a greater impact).

Make the entry of geometry-related features more flexible and versatile

Simulation programs typically require users to define building geometry at the beginning of the simulation process. The prioritized position of geometry entry in the modeling process coupled with the level of detail commonly provided by architectural drawings often seduces modelers into being more faithful to building geometry than to other more influential components of the building model. Furthermore, building plans commonly include lighting plan and other information that span natural HVAC zones, forcing modelers to choose whether to represent more rooms than necessary in building models in order to simplify data entry for these features, or whether they should approximate this data.

The proposed method of facilitating geometry-based features is to allow for different "layers" of entry that the program then automatically converts into the appropriate data format for simulation. For example, when entering long banks of lights that have a per-foot power rating, modelers typically have to calculate the wattage located in each thermal zone. Instead, the modeler could switch to a geometric mode for lighting entry, accurately place the light bank in the plans, and then the program would determine the lighting power that would fall in each thermal zone. This approach would also be relevant for windows that span thermal zones and any other feature that is split across thermal zones or spaces.

It is intended that the layer approach to geometry entry will improve the modeler's understanding of what geometry is and is not significant for. Additionally, if geometries can be layered on as needed, modelers would be less incentivized to be precise with geometry from the beginning of the modeling process, while maintaining the ability to change geometric features, such as thermal zoning, later in the design process.

This change would have moderate direct impact on modeler uncertainty, as it would primarily affect only a portion of Class 3 and Class 2 inputs. However, it should be noted that this flexibility with geometry entry would greatly facilitate future modeler uncertainty research, since one of the primary challenges of this research was the comparison of one modeler's spaces and zones to another's.

Clear demonstration of the data modelers have entered

Maxion and Reeder (2005) and Cranor (2008) emphasized the importance of providing feedback to users regarding the decisions they had input. Modelers should be able to spot typographical errors at a glance, and intuitively overview the information they have entered. For example, lighting levels could be graphically displayed to the user (i.e. rooms would be tinted according to the lighting power present in each space), or a flag could be raised on any space that deviates from code or surrounding rooms by a certain percentage. Similarly, thermal mass could be represented as mixed quantities of chairs, tables, books, etc.

The impact of this feature would primarily protect against errors (that is, unintentional data entry rather than purposeful entry) in all classes of inputs.

FUTURE WORK

The UI design features described in this work were based on the results of an experiment with a particular combination of modelers, simulation program, and building specifications. While future research in BES UI design should include additional user testing under different conditions, it should also be complemented by inspection techniques - Nielsen (1993) discusses how user testing and inspection both find problems that the other method does not. Among the methods outlined in (Nielsen, 1993), problematic BES UI features are likely be discovered through cognitive walkthroughs (envisioning what a typical user would experience while modeling a building) and feature inspection. After identifying problematic features through both user testing and inspection, the effective UI communication strategies put forth by Cranor (2008) can be implemented to mitigate user uncertainty. Features that perform as poorly (or worse) under the new UI could be further iterated on.

After the widespread establishment of BES UIs that minimize modeler uncertainty, it will be worthwhile to re-evaluate the performance of BES predictions as compared to existing building stock.

Method of Test for UI's

Having a method of test for simulation tool UI's that generated one or more performance metrics would be useful in at least two ways:

- Potential users of a particular simulation tool could use it to help assess that tool, just as ASHRAE Standard 140 (ANSI/ASHRAE, 2014) can be used to help assess simulation engines
- Simulation tool developers could use it to evaluate improvements to their UI's. Use of the methods described in this paper could help isolate problems in the UI, e.g. areas of ambiguity. Comparison of performance metrics measured before and after the modifications made in response to problems identified would indicate how successful the modifications had been.

Further work would be required to define and test performance metrics - one possibility would be to use normalized standard deviations from baseline results for output variables of interest obtained from experiments such as the one described above - and to determine the size of the group of users required to produce a particular level of repeatability.

CONCLUSION

As simulation programs begin to implement recommended UI design changes and professional energy modelers begin to use them, it is expected that uncertainty caused by the modeler will drop significantly. In the absence of so much modeler uncertainty, it is further expected that large scale analyses of BES uncertainty will be facilitated by the increase in consistency between modelers. Since modeler uncertainty is not tied to the physics of the building, it is likely to be particularly responsible for obscuring sources of uncertainty in building energy models. When these are diminished, the physical problems should become easier to tease out of existing data.

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