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TOWARDS BETTER PREDICTION OF BUILDING PERFORMANCE: A WORKBENCH TO ANALYZE UNCERTAINTY IN BUILDING SIMULATION

Benjamin D. Lee[1], Yuming Sun[2], Godfried Augenbroe[2], Christiaan J.J. Paredis[1]
[1]Model-Based Systems Engineering Center, Georgia Institute of Technology, Atlanta, USA
[2]College of Architecture, Georgia Institute of Technology, Atlanta, USA

ABSTRACT

In this paper, the authors present the Georgia Tech Uncertainty and Risk Analysis Workbench (GURA-W), a software toolkit that explicitly captures uncertainty about the physical properties of the building and the energy models used to predict its performance. The workbench provides a UQ Repository, giving energy modellers direct access to previously quantified uncertainty distributions for a variety of parameters and models. The workbench also provides automatic identification and modification of parameter values in the input file for the simulation. Together with an intuitive user interface, these capabilities serve to increase the ease with which uncertainty and risk analysis is performed. As such, the methods become more accessible to the building design and retrofit profession at large, rather than being restricted to uncertainty analysis researchers. The predictions developed can serve as a basis for downstream risk-conscious design and retrofit decisions, for instance as part of contractual protocols for improved building performance.

INTRODUCTION

For decades, researchers and practitioners have developed ever more sophisticated simulations of the behavior of buildings. They allocated significant effort in establishing a variety of highly detailed and specialized modules for a range of different materials, systems, heat transfer phenomena, electrical equipment, and occupant behavior. As a result, simulation programs are now able to make estimations about the performance of a building under a wide range of scenarios. Yet these simulations are still mostly deterministic predictions about uncertain future events, relying on information about the present as certain, even if this is not justified. Further, uncertainty about the accuracy of the increasingly specialized modules in energy simulation tools is seldom quantified, let alone available to the general user base.

Case studies that propagate the combined effect of uncertainty through building simulation models have provided evidence that explicit consideration of uncertainty is relevant in many cases, ranging from the design of off-grid buildings (Hu, 2009, Lee, et al., 2012) to energy retrofits (de Wilde, et al., 2002, Heo, 2011 , Hu, 2009, Sun, et al., 2011) to the risk of mold growth (Moon, 2005). In addition, it has been suggested that explicit consideration of uncertainty is of importance to quantify risk measures for a variety of scenarios, including:

- Energy Savings Performance Contracts
- Issuing Guarantees for LEED Certification
- Certifying Ultra-Energy Efficient Buildings
- Reduced Availability Power Contracts
- Evaluating Reduced Availability Power Contracts
- Peak Power Tariff Avoidance Strategies

Each of these scenarios have two common aspects. First, they consider the design, retrofit, or evaluation of a given building or group of buildings. Second, in each scenario at least one party is subject to significant (financial) risk resulting from uncertainty in the performance of the building or building stock or proposed strategy.

When faced with risk in such situations, it is generally regarded that more information is always better, or at least not worse (Hazelrigg, 2003, Pareto, 1971). This notion is reinforced through the understanding that a rational decision-maker will act based upon all of the information at his or her disposal. As such, a rational decision-maker should seek to gain as complete a state of information as possible. Additional information cannot guarantee that a decision will result in a good outcome; but it can increase the likelihood of the decision being a good one, in turn increasing the likelihood of a good outcome. Hence, we argue that decision makers (i.e. the stakeholders in the mentioned scenarios) should rely upon probabilistic rather than deterministic models.

In spite of this recognition, we concede that the adoption of Uncertainty Analysis (UA) into the mainstream building design profession and energy contracting business will depend on the availability of robust and automated environments for building energy models. In this paper, the authors seek to meet this challenge by introducing the Georgia Tech Uncertainty and Risk Analysis Workbench (GURA-W). The goal of the workbench is to empower decision-makers by allowing them a high degree of flexibility in expressing uncertainty, while still providing them with access to rigorously defined uncertainty distributions if desired.

The remainder of this paper is organized as follows: In the next section, the authors provide a background on other workbenches which have been proposed, and identify opportunities for improvement. Then, the GURA-W is introduced and its process flow is explained. Next, a series of three case studies are provided that display the functionality of the workbench. Lastly, concluding remarks are made and opportunities for future work are identified.

BACKGROUND

Previous Work in UA

Some of the early work in exploring UA capabilities in the field of building simulation was done by (de Wit and Augenbroe, 2002, Gero and Dudnik, 1978, Jiang and Hong, 1993, Macdonald and Strachan, 2001). Among these UA studies, de Wit and Augenbroe (2002) developed a framework for decision-making based around propagation of input parameter uncertainty using Latin Hypercube Sampling (LHS) of a custom thermal building model. Since, other researchers have built sampling tools for various simulation engines to support sample-based UA. For example, Modelica (Burhenne, et al., 2010), normative simulation models (Heo, 2011), EnergyPlus (Eisenhower, et al., 2011, Kim, et al., 2011), or other tools (Hopfe, et al., 2007).

Except the work by Eisenhower (2011) none of the above efforts have led to a generic platform to do UA. Some general purpose UA tools have been developed outside of the building simulation community, such as (Andrianov, et al., 2007, Malone and Papay, 1999, Wojtkiewicz, et al., 2001).

The vast majority of these tools are similar in the process by which they quantify uncertainty in some quantity of interest in the output. First, a set of model inputs are designated as uncertain, and then a parametric distribution (usually Gaussian or Uniform) is applied as a quantification of that parameter's uncertainty. Next, a specialized program-wrapping script is defined so that the parameter uncertainties can be propagated automatically through some simulation model via Monte Carlo sampling.

In most current platforms, the user is forced to quantify uncertainty in parameters for which he or she may not have much experience. The user must then manually tailor the wrapping script to the specific instance, leading to possible transcription errors, and minimizing the possibility of future reuse. In addition, it is likely the user will only include a portion of the complete set of uncertain variables, even in initial screenings of parameters; the effort required to include each additional parameter in the wrapping script and then define a distribution could be cumbersome to the point of fatigue. This is indeed the case of performing UA for dynamic building energy models, e.g., EnergyPlus, which contain hundreds of uncertain input parameters accessible in the input file, called IDF. Therefore, it is beneficial to develop a dedicated building simulation tool for UA by creating an integrated UA platform that includes parameter UQ, sampling, propagation, and post-processing capabilities. Such an integrated environment may not only enhance the quality of UA by embedding a reference parameter UQ database, but it also helps to bridge the gap between researchers and practitioners through an integrated user-interface design. Offering this integrated UA environment differentiates our tool (GURA-W) from others that instead focus on parametric analysis, i.e., jEplus (Zhang, 2009), DesignBuilder (DesignBuilder, 2006), OpenStudio (Guglielmetti, et al., 2011), etc.

Lastly, following the terminology of Draper (Draper, 1995) and Hodges (Hodges, 1987), uncertainty about a prediction made using a model can be allocated into two parts: Structural (model) Uncertainty, and Input (parameter) Uncertainty. Whereas almost all UA tools allow some expression of Input Uncertainty, few of the tools surveyed offer some form of quantification of the Structural Uncertainty introduced by the energy model itself. It is this set of deficiencies that motivated the development of the Georgia Tech Uncertainty and Risk Analysis Workbench, which is introduced in the next section.

THE GURA-W

There are three key aspects that motivated the development of the Georgia Tech Uncertainty and Risk Analysis Workbench (GURA-W):

1. <u>Parameter and Structural Uncertainty</u> - The GURA-W should include the ability to include uncertainty introduced by the energy model, in addition to the standard parameter uncertainty
2. <u>Automation</u> - The GURA-W should maximize ease of use by automating the quantification of input uncertainties.
3. <u>Flexibility</u> - The GURA-W should acknowledge that that predictions should be specific to a context, and therefore always allow the user to override any automated process or quantification.

Early in the process, the desire for flexibility led to the modularization of the UA process; an all-in-one tool would be very easy to automate, but then users would be limited in where and how they could override defaults introduced by the workbench. As such, the entire UA process was broken down into a set of individual steps that either occur in series or parallel. Each step was then designated as an

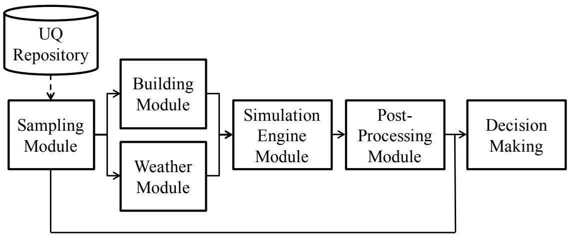

Figure 1. Separation of tasks into modules for the GURA-W

individual module, giving users complete control of information at interfaces (inputs and outputs). Figure 1 shows the set of planned module separations, as well as how they interact. The modules were developed within ModelCenter, a model integration framework, using an open API java interface (Malone and Papay, 1999). Additional functionality is provided by an UQ Repository, with an interface created through Microsoft Excel. The next section will describe each module, detailing the state of information at each interface, as well as the internal processes occurring.

Module Descriptions

Simulation Engine Module - Of primary importance in any simulation workbench is the capability to execute the simulation program given a set of inputs. While the approach used to develop the UQ capabilities is generic, the authors have focused on implementation for EnergyPlus V7.0.0 in the current release. The simulation requires two text input files, one specifying the weather context for the simulation, and another specifying the geometry, construction, and operation of the building and its systems. The module specifically calls the *RunEPlus.bat* batch executable file, which is included in the standard release of an EnergyPlus

Table 1.
Models for which Structural Uncertainty is investigated in initial release

Description	Required Alteration of IDD and Executable
Convection Coefficient Calculation (Interior)	Yes
Convection Coefficient Calculation (Exterior)	Yes
Site Wind Speed Calculation	Yes
Infiltration Calculation (Low Rise Building)	Yes
Internal Mass Effect	Yes
Temperature Gradient Calculation	Yes
Thermal Bridge Effect	No
Urban Heat Island Effect	No
Ventilation Calculation (Single Side)	Yes
Wind Pressure Calculation (Low Rise Building)	Yes

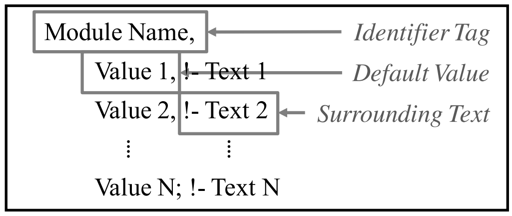

Figure 2. Description of information required to create Building Module IDF parsers

distribution. In order to account for the structural uncertainty from certain models the *EnergyPlus.exe* and *Energy+.idd* files were modified using the EnergyPlus developer's toolkit (See Table 1 for a complete list of models for which structural uncertainty has been assessed. See (Sun, et al., 2011) for more detailed description of methodology for modifications).

Post-Processing Module - The Post-Processing Module is responsible for parsing the various output files that are exported by the Simulation Module. These post-processors are themselves defined in a modular nature, such that energy modellers can select exactly in which outputs they are interested in capturing uncertainty. Standard outputs include cooling or heating loads, electricity or natural gas consumption, and temperature and comfort profiles.

Building Module - The Building Module is responsible for handling any parameter that is uncertain in the construction, operation, or physics of the simulation. In the current release, which has been implemented specifically for EnergyPlus, the Building Module is specifically responsible for parsing any parameter defined in the IDF. In order to accomplish this, a parser is developed for each type of module in an IDF. As seen in Figure 2, the parser searches for occurrences of a given identifier tag, which then initiates automated parsing of the variables contained within the module. The values, which are either numeric or text, are then stored for manipulation in the GURA-W. Once one of these parsers is defined for a given module type, any occurrence of the module type in any target IDF will be automatically parsed by the Building Module. Once any given set of parameters have been automatically parsed and introduced into the ModelCenter environment, the designer is capable of easily changing the value manually, either by using any of ModelCenter's in-built tools, or through the use of the Sampling Module, which is introduced below. The module then recreates a text version of the IDF for execution by the Simulation Module.

An additional task of the Building Module addresses the definition of construction material instances. For many modelers, it is convenient to specify a single definition of a construction material, and then to apply that definition throughout the entire building for every instance of that material. In deterministic simulation, where every material property is assumed

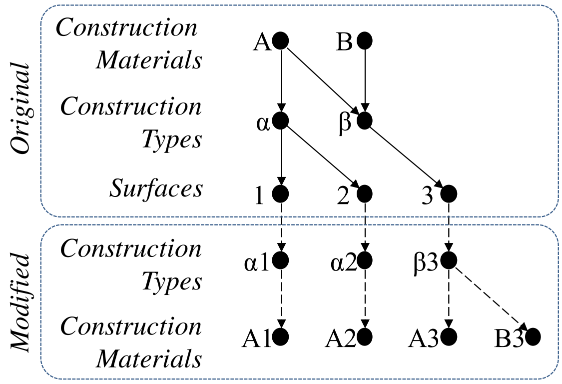

Figure 3. Depiction of Building Module process used to address material

as perfectly known, this assumption of uniformity is generally acceptable. However, when uncertainty is considered, the uniformity assumption requires that all construction materials are identical, ignoring "within batch" uncertainty. The implications of this required assumption are investigated further in the case studies later in this work, but here we will quickly explain the process which the Building Module uses to create a unique material type for each instance, if desired.

The Building Module first creates a network of objects that includes all originally defined *Construction Materials*, *Construction Types*, and *Surfaces* as shown in Figure 3. Then, a new set of *Construction Types* is created for each *Surface*[1]. Once this step is done, the last step is to define a new, instance-level set of *Construction Materials*, each corresponding to a different location throughout the building. The *Surfaces* are not modified during this process, except to update the name of the updated corresponding *Construction Type*. The result is a new IDF that contains the modified network of *Construction Materials* and *Construction Types* instances.

Weather Module- The Weather Module is responsible for handling any uncertainty or variability in local weather that the designers wish to consider. In the current release for EnergyPlus, the Weather Module is specifically responsible for parsing and altering values defined in the Energy Plus Weather file (EPW). The variability in weather can arise from the incorporation of microclimate effects such as the Urban Heat Island effect (Sun, et al., 2011) or the utilization of Stochastic Meteorological Years (Lee, et al., 2012) to quantify the uncertainty in weather variation. The module then creates a text replication of the EPW for execution by the Simulation Module.

Sampling Module - The previous modules have been mainly concerned with meeting the flexibility requirement. Using only these modules, the user is capable of setting the value for any parameter in any way wished, either manually or through the use of ModelCenter's in-built tools. That is not to say that they do not address the automation requirement though; they each automate some portion of an otherwise tedious task of finding and modifying variable values, running simulations, and parsing outputs as well. However, the Sampling Module is primarily concerned with meeting the automation requirement. Rather than forcing users to manually describe several hundred uncertainty distributions, the Sampling Module, in coordination with the UQ Repository, is responsible for importing default distributions for each parameter, based on the parameter type. These default distributions can of course be overridden by the user. The Sampling Module then propagates uncertainty by drawing samples from these distributions, using Latin Hypercube Sampling (LHS) (McKay, et al., 1979).

UQ Repository- The UQ Repository is a set of data files stored in XML format that define default parameter uncertainty distributions as alluded to in the previous paragraph. The repository can be accessed using an interface developed in Microsoft Excel, a portion of which is shown in Figure 4. A unique XML file exists for each modelling scenario. For example, the building investigated in the case study is a low rise building in an urban location on the Georgia Tech campus, so the Urban-Low Rise data file is utilized. In each XML file, a set of information elements is defined for each parameter. First, the information describes whether the parameter is numeric or text, and then clarifies whether the user wishes to consider a numeric value as uncertain. Then, the probabilistic distribution and necessary parameters are stored.

Decision Making- Decision Making is arguably one of the most important functions in using GURA-W. Because decisions are necessarily subjective, the GURA-W cannot directly advise the user what to choose in a context without taking that user's preferences into account. However, it can do the support work for a given number of scenarios to organize the problem for the user, making sure that the important model outputs are accounted for in the correct manner. The decision maker can then be further supported through standardized sensitivity analyses. The automation of such tasks remains ongoing work.

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[1] In actuality, the logic is slightly more complex than this. If one surface is the reverse of another (opposite sides of the same wall) then this must also be taken into account to ensure that identical material instances are used, only in reverse ordering.

		Is this a Number?	Is the number uncertain?	What kind of distribution defines the uncertainty?	Lower Bound, Mean	Upper Bound, St. Dev.	Minimum	Maximum	Are the parameters logical?
Infiltration LowRise	IncludeInfiltrationUQforLowRise	FALSE	FALSE						
	BuildingHeight	TRUE	FALSE						
	BuildingWidth	TRUE	FALSE						
	BuildingLength	TRUE	FALSE						
	ELAPerExteriorArea	TRUE	TRUE	LogNormalAbsolute	-1.6551	0.8767	-999	-999	1
	RFracLeakAreaFloorToCeiling	TRUE	TRUE	UniformAbsolute	0	1	0	-999	1
	XDiffCeilingToFloorLeakArea	TRUE	TRUE	UniformAbsolute	0	1	-1	1	1
Single Side Venti-lation	MethodSelection	FALSE	FALSE						
	DischargeCoefficient	TRUE	TRUE	TriangleAbsolute	0.4	0.65	0.75	1	1
VertTempGrad	IncludeVertTempGradObj	FALSE	FALSE						
	AvailabilityScheduleName	FALSE	FALSE						
	PatternControlScheduleName	FALSE	FALSE						
	ControlIntegerForPatternControlSchedule	FALSE	FALSE						
	Thermostat Offset	TRUE	TRUE	UniformAbsolute	-1	1	-999	-999	1
	ReturnAirOffset	TRUE	TRUE	UniformAbsolute	-2	2	-999	-999	1
	ExhaustAirOffset	TRUE	TRUE	UniformAbsolute	-2	2	-999	-999	1
	TemperatureGradient	TRUE	TRUE	UniformAbsolute	0.5	1.875	-999	-999	1

Figure 4. Portion of Excel interface for accessing XML files in UQ Repository

CASE STUDIES

In this section, a series of case studies are presented to display the capability of the GURA-W to quantify uncertainty in heating and cooling load under a variety of different assumptions about material properties. Three scenarios are chosen primarily to show the versatility of the workbench, not to make use of the results per se.

In scenario 1, it is assumed that material properties are specified by a designer, who then selects a particular retailer to purchase those materials from. The retailer cannot and will not guarantee that the actual supplied materials exactly meet the material properties ordered by the designer. As a result, the supplied materials have material properties that are uncertain. We assume that the uncertainty can be modelled as samples from a Normal distribution, with mean equal to the value specified by the designer, and standard deviation equal to 1% of that value.

In scenario 2, we make the additional assumption that the retailer cannot guarantee that products, even within the same batch, have uniform properties. As such, every instance of each material will have a unique set of material properties, assumed as independent samples from a Normal distribution with mean equal to the value specified by the designer, and standard deviation equal to 1% of that value.

In scenario 3, the full power of the workbench will be explored by including the Structural Uncertainty introduced by 9 model formulations (from Table 1) in addition to the material uncertainty from scenario 2. This scenario is interesting because it provides an opportunity to investigate the impact of neglecting uncertainty which has been quantified.

The building being investigated in all scenarios is the Cherry L. Emerson building, which is located centrally on the Georgia Tech campus. The building was originally constructed in 1959, contains 61 offices and rooms, and is rectangular shaped and oriented with the longer sides facing north-south.

Scenario 1

The IDF for the Cherry L. Emerson building was created using the DesignBuilder front end tool. The model was created using 13 different material types, as well as one additional window type. For the materials, the thickness was assumed to be exact, while the conductivity, density, specific heat, thermal absorptance, solar absorptance, and visible absortances were each sampled from Normal distributions as previously discussed. For the window material, the thickness was again assumed exact, but all other properties were each sampled from Normal distributions as previously discussed. All other parameters were fixed. See Table 2 for a complete list of the material properties considered uncertain in scenarios 1 and 2, as well as description of the number of occurrences of each type.

100 LHS samples were drawn and then propagated through the workbench, completing in slightly less than 1.5 hours. The annual cooling and heating loads for two zones were then tabulated into a set of histograms, as shown in Figures 5(a)-(b). Also plotted (vertical line) are the nominal cooling and heating loads corresponding to the simulation containing nominal values for material properties. As could be expected, the variability of the cooling and heating loads as a result of material property uncertainty is modest, but still significant.

Scenario 2

In scenario 2, the IDF for the Cherry L. Emerson building was modified using the instance process explained in the Building Module section previously. This functionality allows users to automate the process of assigning a unique material definition to each instance occurring throughout the building model. This allows users to investigate the impact of "within batch" uncertainty, as introduced previously.

In scenario 1, 81 variables were included as uncertain. The ease and speed with which the distributions of the samples were developed and then propagated offered a glimpse at the value of GURA-W. By comparison, for scenario 2 1,456 variables were included as uncertain. Including such a large number of variables as uncertain would not have been possible if performed manually. Or at best, doing so would have resulted in numerous transcription errors. Yet the GURA-W was able to automatically develop uncertainty distributions for these parameters and then propagate 100 LHS samples in slightly less than 1.5 hours. Histograms for the cooling and heating loads for the same two zones as scenario 1 are shown in Figures 6(a)-(b). Also plotted (vertical line) are the same nominal cooling and heating loads corresponding to the default values for material properties. For convenience of interpretation, the extent of the horizontal axes (cooling/heating load) are the same for corresponding plots from scenarios 1 and 2.

From observing Figures 5 and 6, we can gain several key insights. First, we note that the approach scales well with the number of parameters. Second, at least for this circumstance, the deterministic simulation reliably returned an estimate extremely close to the mean of the predicted distribution. Indeed, the largest discrepancy between the deterministic estimate and the sample mean in the cooling or heating loads for all 6 zones was 0.28% for scenario 1 and 0.15% for scenario 2. This suggests that while uncertainty in material properties may lead to uncertainty in the actual heating and cooling load, it does not greatly affect the expected value for either.

Thirdly, we note a strange phenomenon, that upon further reflection makes conceptual sense. Relative to scenario 1, it could be said that scenario 2 includes a greater level of uncertainty; it is not assumed that every instance of a construction material is identical. However, we see by looking at Figures 5 and 6 that the variability in the heating and cooling loads are greatly reduced in scenario 2. The standard deviations calculated in scenario 1 are on average 1.81 times greater for the cooling loads, and 2.02 times greater for the heating loads (including all six zones). This reduction of uncertainty seems counterintuitive, but can be explained via covariance. If a model of the heating / cooling load is specified as:

$$load = f(R_1, R_2) \tag{1}$$

where R_1, R_2, are material properties for a similar type of material at different locations in a building, then the model can be approximated by using a Taylor series expansion, at least for small deviations:

$$load = \frac{\partial f}{\partial R_1} R_1 + \frac{\partial f}{\partial R_2} R_2 + f_0 \tag{2}$$

If only R_1, R_2 are considered as uncertain, with f_0 assumed to be scalar, then the variance of the load can be given as (Leon-Garcia, 1994),

$$\sigma_{load}^2 = \left(\frac{\partial f}{\partial R_1}\right)^2 \sigma_{R_1}^2 + \left(\frac{\partial f}{\partial R_2}\right)^2 \sigma_{R_2}^2 + 2\rho \frac{\partial f}{\partial R_1}\frac{\partial f}{\partial R_2}\sigma_{R_1}\sigma_{R_2} \tag{3}$$

where σ_*^2 refers to the variance or covariance of the random variable, respectively, and ρ is the correlation of the random variables. In scenario 1, it was assumed that construction materials were identical throughout the building, and thus the material properties at each particular surface were perfectly correlated with one another, such that:

$$\rho = 1;$$

$$\sigma_{load}^2 = \left(\frac{\partial f}{\partial R_1}\right)^2 \sigma_{R_1}^2 + \left(\frac{\partial f}{\partial R_2}\right)^2 \sigma_{R_2}^2 + 2 \frac{\partial f}{\partial R_1}\frac{\partial f}{\partial R_2}\sigma_{R_1}\sigma_{R_2} \tag{4}$$

while in scenario 2, the construction materials were assumed to be completely independent, and so:

$$\rho = 0;$$

$$\sigma_{load}^2 = \left(\frac{\partial f}{\partial R_1}\right)^2 \sigma_{R_1}^2 + \left(\frac{\partial f}{\partial R_2}\right)^2 \sigma_{R_2}^2 \tag{5}$$

Comparing Equations (4) and (5), it is clear that scenario 2 should have a smaller variance than scenario 1, which is as observed.

Table 2.

Material Parameters for which Parameter Uncertainty is investigated in scenarios 1 and 2

Description	Number of Occurrences
Material,	*(11 Material Types, 142 Instances)*
Conductivity	
Density	
Specific Heat	
Thermal Absorptance	
Solar Absorptance	
Visible Absorptance	
Material:NoMass,	*(2 Material Types, 30 Instances)*
Thermal Resistance	
Thermal Absorptance	
Solar Absorptance	
Visible Absorptance	
WindowMaterial:Glazing,	*(1 Material Type, 44 Instances)*
Solar Transmittance	
Front Side Solar Reflectance	
Back Side Solar Reflectance	
Visible Transmittance	
Front Side Visible Reflectance	
Back Side Visible Reflectance	
Infrared Transmittance	
Front Side Infrared Hemispherical Emissivity	
Back Side Infrared Hemispherical Emissivity	
Conductivity	
Dirt Correction Factor	

Scenario 3

In scenario 3, the structural uncertainty introduced by model formulations is analyzed by propagation. The UQ for each model formulation is based upon the framework laid out in (Sun, et al., 2011). The model formulation descriptions are shown in Table 1.

The results of a 100 LHS sample UQ are shown in Figure 7 (a)-(b). The most important observation relates to the significant offset in both heating and cooling load between the nominal value and sample mean. This is the compounded result of all parameter and structural uncertainties that are considered in addition to the material properties considered in the previous scenario. The main contributors to the uncertainty in the outcomes are undoubtedly the microclimate related phenomena such as wind pressure induced infiltration, heat island effect, wind velocity related external heat transfer coefficients, uncertainty in solar irradiation etc. Future work will seek to further justify these claims through the use of statistical tools for sensitivity analysis.

This brings up the important issue of ascertaining that all relevant sources of uncertainty have been quantified at the start of an uncertainty analysis. We note this as a topic requiring significant attention, but as this paper focuses on the facilitation and mechanics of the UA itself, we leave this for future work.

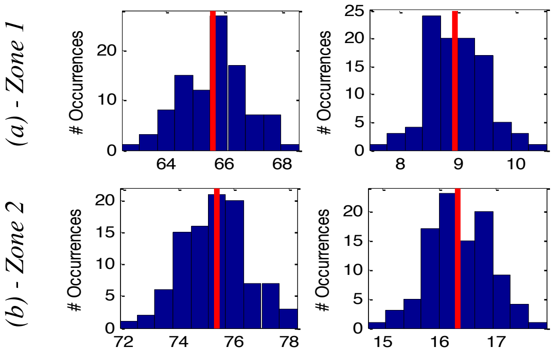

Figure 5 (a)-(b). Annual Cooling (left) and Heating (right) Load (MWh) Distributions for Scenario 1

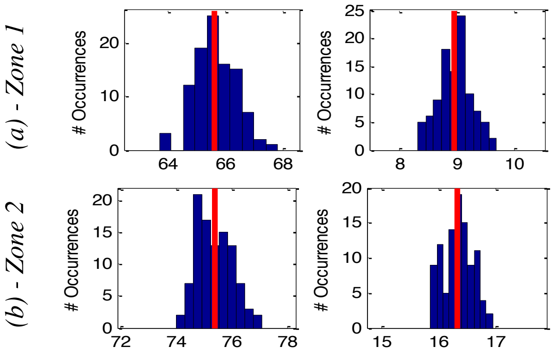

*Figure 6 (a)-(b). Annual Cooling (left) and Heating (right) Load (*MWh*) Distributions for Scenario 2*

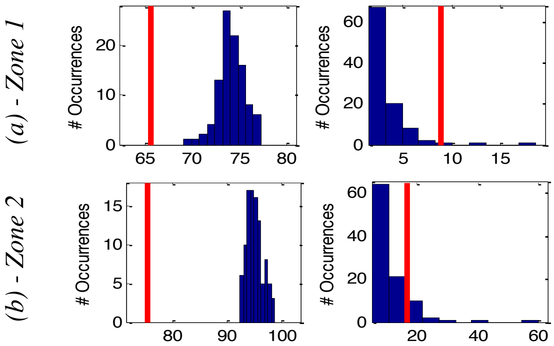

*Figure 7(a)-(b). Annual Cooling (left) and Heating (right) Load (*MWh*) Distributions for Scenario 3*

CONCLUSION

In this work, we have presented the Georgia Tech Uncertainty and Risk Analysis Workbench as a tool to facilitate energy modellers in the quantification and analysis of uncertainty in the energy simulation of buildings. The workbench is motivated by the desire to be able to include uncertainty about the inputs and structure of a simulation model in a flexible and automated fashion. Three case studies were utilized to demonstrate the functionality of the workbench, leading to interesting insights about the impact of different types of uncertainty.

A core value of the GURA-W is the UQ Repository that includes a set of previously quantified uncertainty distributions for numerous parameters and model formulations, currently limited to the EnergyPlus model. Thus, when an energy modeller is faced with quantifying a particular parameter with which he or she has limited experience and would otherwise rely on an uninformed prior belief, he or she could instead leverage the prior work of others to inform him or herself. Future work will seek to increase the extent of the UQ Repository, as well expand the general functionality of the workbench.

NOMENCLATURE

GURA-W = Georgia Tech Uncertanty and Risk Analysis Workbench
LHS = Latin Hypercube Sampling
UA = Uncertainty Analysis
UQ = Uncertainty Quantification

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