(An Energy Analysis Test Case)

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Abstract. Building design decision-making is associated with uncertainties due to variations over time and unpredictable parameters. There is a growing demand for probabilistic methods, i.e., uncertainty and sensitivity analyses to handle the uncertainties in building design. This research intends to encourage the application of Building Information Modeling (BIM) for addressing design uncertainties affecting building energy performance. The mapping between BIM (Revit and Dynamo) and a customized model-based energy analysis tool in Excel is investigated to translate architectural models to energy models and conduct the probabilistic analyses. The application of this method is demonstrated with a test case of a hypothetical residential unit in College Station, Texas, USA. Input variables in this example are the thermal properties of building elements, and the two simulation outputs are annual heating and cooling energy consumption, and deviation from comfort temperature. The results indicate the probability distribution of simulation outputs and the importance factor of each design input. This method deals with uncertainties and provides a more reliable and robust basis for design decision-making.

Keywords. Building design decision-making; Building Information Modeling (BIM); Parametric design; Uncertainty and sensitivity analysis; Building performance analysis.

1. INTRODUCTION

The main sources of uncertainty in building performance analysis are induced by the degradation of building physical and mechanical elements over time, climate change, and occupants' behavior. Conventional building performance simulation tools that use deterministic models to simulate building characteristics and performance are incapable of dealing with uncertainties. The promising development of BIM technologies encourages the application of probabilistic methods in architectural building design to overcome the uncertainties. Built upon our previous research on the implementation of probabilistic methods in building energy analysis (Shahsavari et al. 2018), this paper introduces a framework

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to integrate BIM with uncertainty and sensitivity analyses. This framework includes creating an architectural building model in Revit, and retrieving the input parameters for running the required simulations. The input variables are exported from Dynamo to a spreadsheet-based energy analysis tool to conduct uncertainty and sensitivity analyses. The mean and standard deviation values of input parameters are applied to create a range of values with a known probability distribution. Random samples of the input values are generated, and the simulations are run many times. Using the Monte Carlo approach, the probabilistic predictions of building energy performance are presented in an Excel-based Graphical User Interface (GUI).

In this paper, building design decisions regarding the selection of thermodynamic properties of building materials, provide a case study. Three different design alternatives are designed and compared using this framework. The annual heating and cooling energy consumption (AHCEC), and deviation from comfort temperature (DCT) are the two main output parameters. A hypothetical residential unit in College Station, Texas is selected to demonstrate the application of the proposed framework. The results are discussed to show how architects can use this extra information in building design decision-making.

2. BACKGROUND

2.1. BUILDING INFORMATION MODELING (BIM) FOR PROBABILISTIC ANALYSIS

Parametric modeling tools are increasingly applied in building design and performance analysis (Du et al., 2018; Lim et al., 2015). BIM-based design tools, i.e., Green Building Studio and Insight360 allow integrating building performance analysis with building modeling. Dynamo, a visual programming user interface linked with Revit, allows extracting model information such as geometrical information, quantities, thermal properties of building elements, and cost estimates, from Revit and exporting the data to energy simulation tools (Asl et al., 2015).

3. METHODOLOGY

3.1. OVERVIEW OF THE BIM-BASED PROBABILISTIC FRAMEWORK

This research develops a practical framework to provide a clear guidance on the mapping between BIM tools and probabilistic techniques such as Monte Carlo to improve the robustness of the results in building energy analysis. The parametric capabilities and visual programming interface of BIM tools, i.e., Revit and Dynamo allow the automation of building information collection and sample generations required for probabilistic energy analyses. Three key features of this method, that is referred to as BIM-based PRObabilistic (BIMPRO) framework, are:

1. BIMPRO includes building physical and thermal parameters concerning building energy performance and considers the variations of design inputs as the primary source of uncertainty.

2. BIMPRO is capable of retrieving all the required information from Revit and update the data based on the architectural model.
3. A user can override the input data as needed.

The workflow of BIMPRO framework consists of the following: (1) pre-processing that is a mapping between building model in Revit and probabilistic energy calculation in Excel, (2) sampling and simulation, (3) post-processing, i.e., uncertainty and sensitivity analysis, and (4) evaluation and design decision-making (See Figure 1).

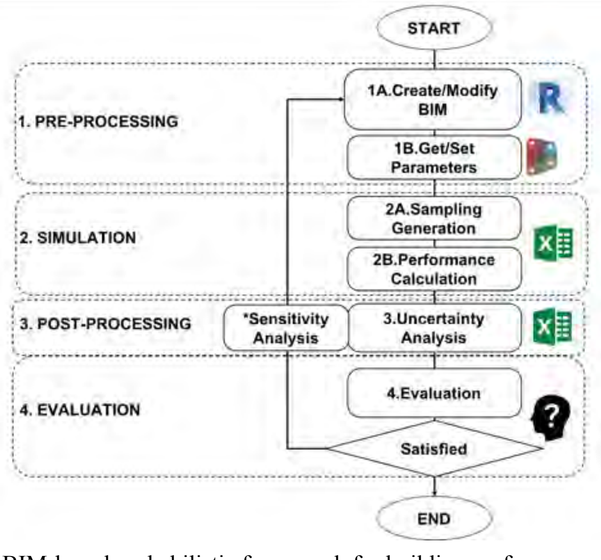


Figure 1. BIM-based probabilistic framework for building performance analysis.

3.2. PRE-PROCESSING

The first step in the BIMPRO is creating a BIM model in Revit. In this phase, building geometry and the thermal properties of material are defined. A standard deviation (stddv.) value for each input parameter will be specified in later phases to perform the probabilistic analysis. The building elements studied in this paper are exterior walls, roofs, floors, and windows.

There are three types of information required in building envelope energy exchange equations: (1) The dimensions of building elements such as height, width, area, and volume; (2) The analytical properties of opaque material including the heat transfer coefficient (U-value), and analytical properties of transparent material consisting of visual light transmittance (VLT), solar heat gain coefficient (SHGC) and heat transfer coefficient (U-value); and (3) The material thermal properties including density, specific heat capacity, and thermal conductivity. The user can define the dimensions and material properties with creating an object family and building materials in Revit. Also, Revit API allows modifying analytical properties with scripting. Figure 2 indicates how to access the physical and thermal properties of building material in a Revit model.

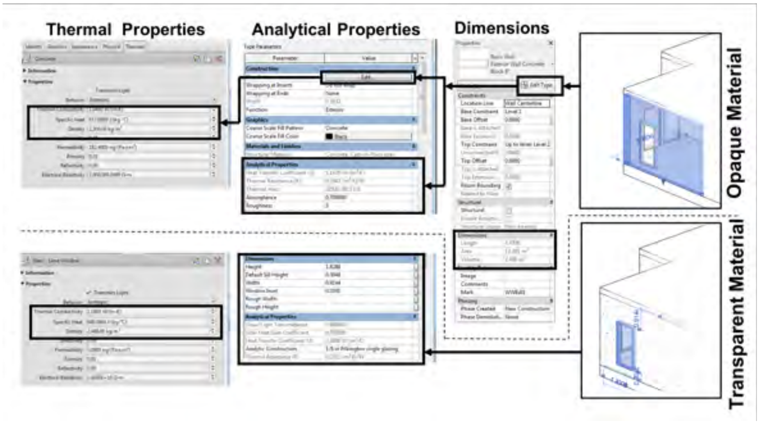


Figure 2. The physical and thermal parameters of building elements accessible in a Revit model.

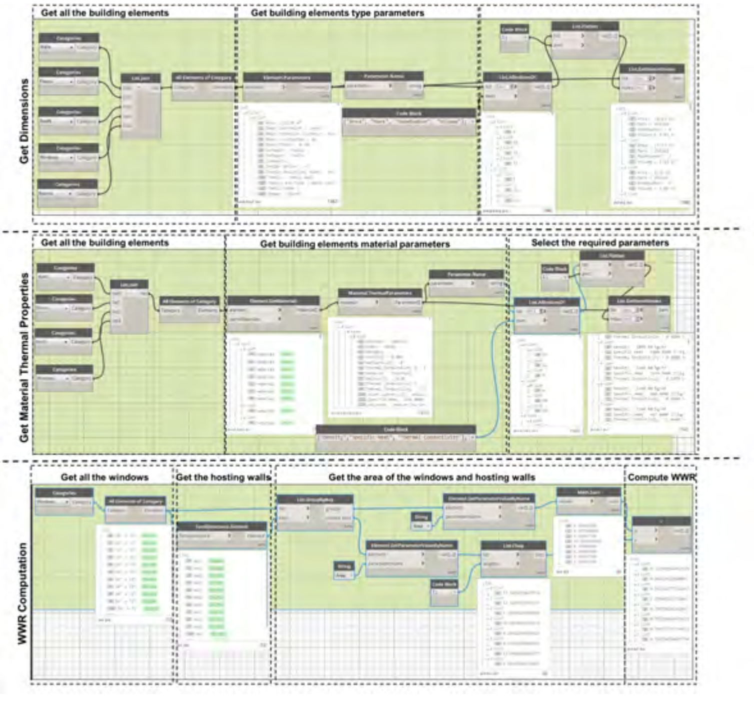


Figure 3. Extracting directly accessible and indirectly accessible parameters from a Revit model in Dynamo.

A mapping between Revit and Excel is performed through Dynamo, to retrieve the input parameters from the BIM model. Building material properties, the dimensions and Window-to-Wall Ratios (WWRs) are transferred from the Revit model to the Excel-based energy consumption calculation tool, developed by (Shahsavari et al., 2018). Each input parameter is in one of the two statuses of directly available and indirectly available parameters. The directly available parameters including building material properties are accessible using built-in nodes in Dynamo, i.e., Element.GetParameterValueByName and Element.GetMaterial. Indirectly available parameters are those that need to be computed using other available parameters. For instance, WWR is not immediately accessible in the Revit model but can be calculated having the area of windows and the area of hosting walls. The user can compute WWRs in Dynamo by dividing the area of windows over the area of the hosting walls. Figure 3 illustrates how to get building dimensions, thermal properties, and WWR in Dynamo.

3.3. SIMULATION

The uncertainty and sensitivity analyses with Monte Carlo methods require the input probability density functions (PDFs) to generate a number of samples, run simulations iteratively, and get the PDF of the outputs. A number of studies integrate the Monte Carlo approaches with EnergyPlus using a set of other software such as jEPlus and MATLAB (Delgarm et al., 2018; Bordbari et al., 2018). This BIMPRO framework applies a Excel-based user interface for generating the samples, running the simulations and presenting the results. This integrated platform to do UA will eliminate the risk of data loss and errors due to data transfer among different software.

A model-based energy calculation tool is developed in FORTRAN, with a Graphical User Interface (GUI) in Microsoft Excel. The Resistance-Capacitance modeling method (Shahsavari et al., 2018) is applied to model building physics in a steady state. The outputs of this tool are building annual heating and cooling energy consumption (AHCEC), and deviation from comfort temperature (DCT). The spreadsheet-based GUI allows importing the input data from Dynamo to Excel and conducting the probabilistic analyses.

The user selects the mechanical parameters, i.e., HVAC efficiency and heating/cooling power from the predefined drop-down menu in the spreadsheet-based tool. Besides, the weather data in the .csv format is required to run the simulations. The user can get the EnergyPlus weather (epw.) file from the EnergyPlus website and import it to Excel using a text import wizard tool. The Typical Meteorological Year (TMY) or the actual weather data can both be applied in this model.

Using this BIMPRO GUI, the user can define a standard deviation (stddv.) value associated with each input parameter. The expert judgment or defined values in previous research are good sources of information for selecting realistic stddv. values. Figure 4 depicts an overview of the BIMPRO GUI in Excel.

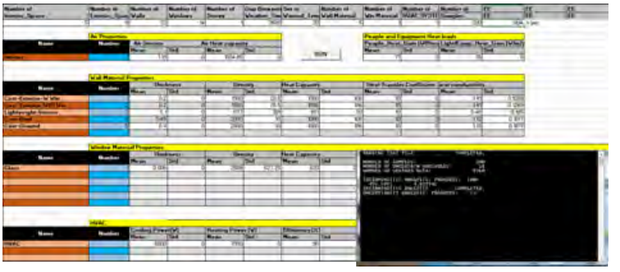


Figure 4. An overview of the BIMPRO GUI in Microsoft Excel.

3.4. POST-PROCESSING

The post-processing phase in this framework consists of a graphical presentation of uncertainty and sensitivity analysis using the Central Limit Theorem and the Morris method, respectively (Ott and Longnecker, 2015). Architects can implement these results in their decision-making as extra information to get an insight into the effects of uncertainties on the building performance.

3.5. EVALUATION

The probability distribution of AHCEC and DCT provide decision-makers with a better prediction of the possible range of building performance. Also, sensitivity analysis result identifies the most impactful design variables and facilitates the search for the best possible design alternative.

4. TEST CASE

4.1. MODEL DEFINITION

This paper reports a test case of a hypothetical residential unit in College Station, Texas, USA to display the application and capabilities of BIMPRO. In this test case, three sets of envelope material with different thermal properties are assigned to a hypothetical building model. The BIMPRO is applied to evaluate these three design alternatives and identify the one with best predicted performance. Figure 5 (a) and (b) show the floorplan and 3D view of the model base case.

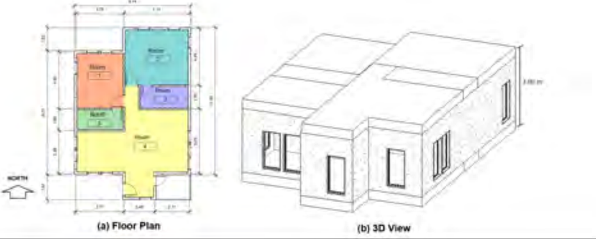


Figure 5. (a) The floor plan and (b) The 3D view of model base case.

Table 1 indicates value assumptions for the thermal properties of building material, including density, heat capacity, and thermal conductivity. These assumptions are extracted from (MacDonald, 2002), to design three different envelope alternatives for the test case. Building envelope elements, i.e., exterior walls, roof, floor, and windows are discussed in this analysis. The uncertainty and sensitivity analyses are conducted to evaluate the three alternatives and select the best option to fulfill building energy efficiency.

Table 1. The thermal properties of building envelope materials in three different design alternatives (MacDonald, 2002).

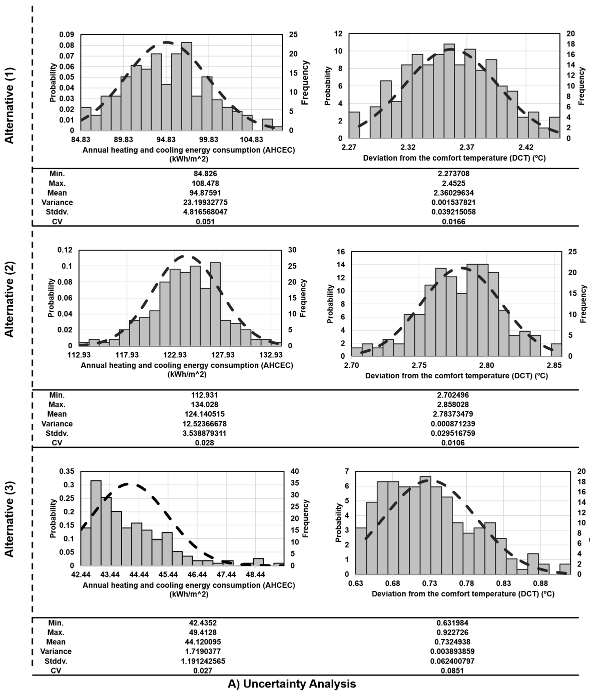
Design Alternative	Building Element	Material Type	Density ρ (kg/m^3)		Heat Capacity c_p (J/kgK)		Thermal Conductivity λ (W/mK)	
			Mean (μ)	Stddv. (σ)	Mean (μ)	Stddv. (σ)	Mean (μ)	Stddv. (σ)
Alternative 1	Exterior walls	Concrete	1900	28.5	1000	106	1.41	0.1269
	Roof	Concrete	2000	30	1000	106	1.13	0.1017
	Floor	Concrete	2000	30	1000	106	1.13	0.1017
	Windows	Clear glass	2509	105	820	50	1.294	0.09
Alternative 2	Exterior walls	Clay Brick	1720	172	837	83	0.789	0.07
	Roof	Metal	6278	627	544	54	224	22
	Floor	Timber	648	64	1845	184	0.201	0.02
	Windows	Plate Glass	2515	8	828	33	0.95	0.067
Alternative 3	Exterior walls	Plywood	622	26	1718	128	0.16	0.028
	Roof	Asbestos boards	1488	501	958	109	0.43	0.153
	Floor	Timber + carpet	831	85	3585	330	0.801	0.028
	Windows	Glass Fiber quilt	32	3	851	57	0.035	0.003

Other input parameters in this energy calculation model are assumed as follows: A one-person occupant load is set for rooms 1, 2, 3, 5 and three-person occupant load for room 4. The main internal heat gain coefficients are occupant loads=15W per person, lighting loads=15 W/m^2 and equipment loads=35 W/m^2. For the outside air temperature, the model uses the actual weather data of the year 2015. An HVAC system using a closed-loop PID controller maintains a comfortable temperature for the inside air, i.e., 21°C. The HVAC system is assumed to work with 75% efficiency.

4.2. RESULTS AND DISCUSSION

Two hundred samples are generated for each design input. The building performance metrics, i.e., AHCEC and DCT are calculated using BIMPRO framework. The frequency histograms shown in Figure 6 compare the predicted AHCEC and DCT for three design alternatives, described earlier. The AHCEC and DCT result for each design alternative is summarized with minimum (Min.), maximum (Max.), mean, variance, standard deviation (Stddv.), and coefficient of variance (CV). Design alternative (3) shows the best performance, with the lowest mean and coefficient of variance. This performance is achieved in design alternative (3), as a result of using a better combination of envelope materials in terms of thermal properties.

The coefficient of variance (CV) that is the ratio of the standard deviation to the mean is as significant as the mean value. This measurement indicates the difference between an observed data and their mean value and determines the level of confidence in a building performance prediction. Note the conventional deterministic tools only deliver the mean value of the output, as they do not deal with uncertainties in the building design process. Furthermore, the building model is too complex to estimate the variance of the output by just reviewing the variance of the input parameters. Thus, performing an uncertainty propagation for identifying the probability distribution of the output and obtain the variance supports handling the uncertainties.



Alternative (1)	AHCEC	DCT
Min.	84.826	2.273708
Max.	108.478	2.4525
Mean	94.87591	2.36029634
Variance	23.19932775	0.001537821
Stddv.	4.816568047	0.039215058
CV	0.051	0.0166

Alternative (2)	AHCEC	DCT
Min.	112.931	2.702496
Max.	134.028	2.858028
Mean	124.140515	2.78373479
Variance	12.52366678	0.000871239
Stddv.	3.538879311	0.029516759
CV	0.028	0.0106

Alternative (3)	AHCEC	DCT
Min.	42.4352	0.631984
Max.	49.4128	0.922726
Mean	44.120095	0.7324938
Variance	1.7190377	0.003893859
Stddv.	1.191242565	0.062400797
CV	0.027	0.0851

Figure 6. Uncertainty analysis results for three building design alternatives .

Using the empirical rule (Ott and Longnecker, 2015), the confidence intervals of design predictions are described as follows: according to Figure 6, we are 95% confident that the AHCEC output of alternative (3) would be in a range of (40.74, 47.52). Alternative (3) has the least variance in the AHCEC results compared to alternative (1) and (2), and this gives the designer higher confidence about the output predictions of this design alternative.

Sensitivity analysis result, shown in Figure 7 identifies the level of contribution of each design variable on the variations of building AHCEC and DCT. Sensitivity indexes associated with thermal properties of the material in each building element are superpositioned in one factor. For instance, the sum of sensitivity indexes of density, heat capacity, and thermal conductivity of windows are referred to as “windows” in Figure 7. The results show that window material has the most significant impact on the amount of building AHCEC and DCT. The effects of thermal properties of roofs are second only to those of windows in both AHCEC and DCT analysis. Next, the walls without windows and floors have a roughly equal effect on variations of AHCEC, while floors are more important than walls without windows in their effects on the DCT. Walls with windows are the least significant parameters in both AHCEC and DCT analysis.

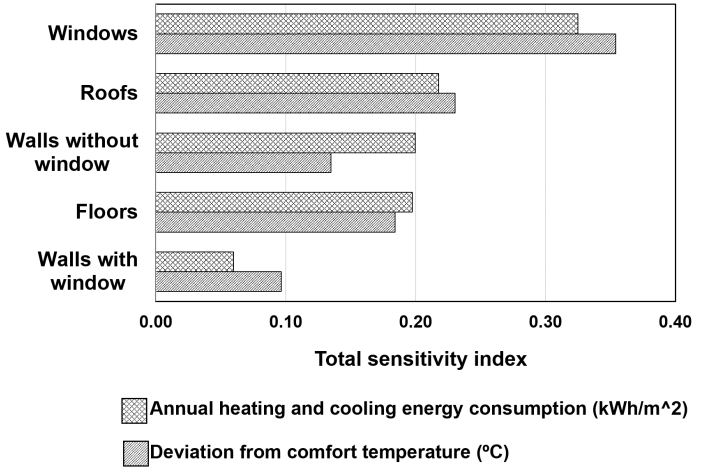


Figure 7. Sensitivity analysis results of the building base model.

5. CONCLUSION

This paper studies the uncertainty propagation of building energy models and introduces the BIMPRO framework and associated prototypes created in Dynamo and Excel to facilitate the application of probabilistic methods in architectural design. The innovation of this framework is a mapping between BIM and probabilistic analysis tools. The mean, variance and confidence intervals obtained from uncertainty analysis provide an evidence-based basis for design decision-making and thus, improve the architects' confidence in decision making. Also, sensitivity analysis result enables designers to identify design variables with the highest impact on the outputs, to enhance the efficiency of building design optimization.

One of the limitations of this work is that the user is required to input the stddv. values into the Excel GUI, manually. A database of building material parameters with mean and stddv. is required to be accessible by BIM, energy analysis, and building lifecycle analysis (LCA) tools, to facilitate the whole process. Having this database will allow further development of this framework to use capabilities of Dynamo to access the mean value and stddv. of the input parameters and create a normal probability density function for each design parameter. Also, conditional probability and how the individual input variables might affect each other, also the final output requires more investigation to support informed design decision-making.

References

Asl, M.R., Stoupine, A., Zarrinmehr, S. and Yan, W.: 2015, Optimo□: A BIM-Based Multi-Objective Optimization Tool Utilizing Visual Programming for High Performance Building Design, *Proceedings of eCAADe 2015*, 673-682.

Bordbari, M.J., Seifi, A.R. and Rastegar, M.: 2018, Probabilistic Energy Consumption Analysis in Buildings Using Point Estimate Method, *Energy*, **142**, 716-722.

Delgarm, N., Sajadi, B., Azarbad, K. and Delgarm, S.: 2018, Sensitivity Analysis of Building Energy Performance: A Simulation-Based Approach Using OFAT and Variance-Based Sensitivity Analysis Methods, *Journal of Building Engineering*, **15**, 181-193.

Du, J., Zou, Z., Shi, Y. and Zhau, D.: 2018, Zero Latency: Real-Time Synchronization of BIM Data in Virtual Reality for Collaborative Decision-Making, *Automation in Construction*, **85**, 51-64.

Lim, Y., Shahsavari, F., Azli, F., Ossen, D. and Ahmad, M.: 2015, Developing a BIM-Based Process-Driven Decision-Making Framework for Sustainable Building Envelope Design in the Tropics, *International Conference on Building Information Modelling (BIM) in Design, Construction and Operations*, Bristol.

MacDonald, I.A.: 2002, *Quantifying the Effects of Uncertainty in Building Simulation*, Ph.D. Thesis, University of Strathclyde.

Ott, R.L. and Longnecker, M.T.: 2015, *An Introduction to Statistical Methods and Data Analysis*, Nelson Education.

Rezaee, R., Brown, J., Augenbroe, G. and Kim, J.: 2015, A New Approach to the Integration of Energy Assessment Tools in CAD for Early Stage of Design Decision-Making Considering Uncertainty, *Proceedings of the 10th European Conference on Product and Process Modelling, ECPPM*, 367-373.

Shahsavari, F., Koosha, R., Vahid, M.R., Yan, W. and Clayton, M.J.: 2018, Towards the Application of Uncertainty Analysis in Architectural Design Decision-Making, (A Probabilistic Model and Applications), *Proceedings of eCAADe 2018*, Lodz, Poland, 295-304.