

INTEGRATING PROBABILISTIC METHODS INTO BIM AND PARAMETRIC  
MODELING FOR PERFORMANCE-DRIVEN BUILDING DESIGN AND RISK  
ASSESSMENT

A Dissertation

by

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## ABSTRACT

This research addresses the challenges associated with conventional methods of performance-based building design, i.e., ignoring the existing uncertainties and lacking a systematic framework to incorporate risk assessment in building performance analysis. The goal of this research is to tackle data uncertainties and potential risks in architectural design decision-making with a focus on building energy performance.

A novel framework (BIMProbE) is created for integrating Building Information Modeling (BIM) into probabilistic building energy simulation to enhance the user interface and system interface for such simulations. In this research, BIM tools and BIM API are used to create probability distributions of material thermal properties for the building energy simulation. The present work enables a probabilistic BIM for energy simulation and future other building performance simulations. Also, BIM and parametric design tools (as the two major tools allowing a change of architectural design method) are used together for probabilistic design decision making.

The proposed framework is tested with three energy evaluation test cases. In each test case, building annual thermal load is measured for three different design options using deterministic and probabilistic methods. Also, three design decision making criteria including expected value, maximax, and maximin are applied to discuss the simulation results based on different attitudes towards risk. Different probabilistic distributions of input variables (normal or Poisson) are used in each test case. The thermal properties of building materials, building internal heat loads, HVAC system specifications, and some

aspects of occupant behavior are considered as uncertainties to predict the probability distribution of building annual thermal load.

The results show that compared with the existing deterministic method for architectural design, using probabilistic methods is possible to result in significantly different design decisions to be made or different design options to be selected. Therefore, probabilistic methods should be considered in design simulation and decision-making. Furthermore, the extra information obtained from the probabilistic approach, including the mean, standard deviation, and variance, could help predict the possible range of the outcome for each design option. This research concludes that investigating probabilistic architectural design methods forms a major future research area in computational design.

## DEDICATION

This dissertation is dedicated to Maman, Baba, and Rasool, whose love was my power to grow.

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## NOMENCLATURE

HVAC	Heating, Ventilation, and Air Conditioning
BIM	Building Information Modeling
API	Application Programming Interface
BPS	Building Performance Simulation
UA	Uncertainty Analysis
LHS	Latin Hypercube Sampling
FMEA	Failure Mode and Effect Analysis
KPI	Key Performance Indicators
KRI	Key Risk Indicators
DSC	Design Space Construction
GURA_W	Georgia Tech Uncertainty and Risk Analysis Workbench
EV	Expected Value
GUI	Graphical User Interface
BIMProbE	BIM-based Probabilistic framework
WWR	Window-to-Wall Ratio
SHGC	Solar Heat Gain Coefficient
SIP	Structurally Insulated Panel
VT	Visible Transmittance



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## CHAPTER 1

### INTRODUCTION

The building sector currently represents the highest amount of energy consumption [1] and according to [2] the energy used for heating, cooling and lighting in buildings is the primary source of carbon emissions in developed countries. Building design decision-making for better performance is a significant concern in the building industry. However, performance-driven building design optimization is inevitably associated with uncertainties induced by climate change, complex behavior of occupants, and physical degradation of building materials and Heating, Ventilation, and Air Conditioning (HVAC) systems over time. A growing demand for handling uncertainties in building design decision-making has challenged conventional design methods. Thus, researchers in this field lean towards viable alternatives to using deterministic design methods, e.g., probabilistic methods [3].

The probabilistic methods, including uncertainty analysis techniques introduce a potential to represent uncertainties and specify probability distributions of input parameters, and relative frequencies of the outcomes, rather than some deterministic magnitudes. Characterizing the distributions of simulation outcomes with statistical measures including but not limited to mean, standard deviation, and variance helps provide more information to improve the process of performance-driven building design decision-making. Different decision-making criteria such as expected value, maximax, and maximin could support design decision-making with different attitudes towards risks.

This research presents a new framework to implement probabilistic methods in the field of performance-driven building design decision-making, using parametric modeling and Building Information Modeling (BIM). Adding probability distributions of design input parameters using BIM's Application Programming Interface (API) is proposed to refine design optimal solution set based on probabilities and provide a more robust basis for building performance prediction and design decision-making. This study demonstrates the development of the proposed framework and evaluates its validity with experiments and prototypes considering several sources of uncertainties in building performance analysis.

### **1.1 Research Problem and Questions**

Building Performance Simulation (BPS) tools are useful in the field of building design optimization and provide results but fail to deal with uncertainties. Different sources of uncertainties affect the building performance prediction, and actual performance. The commonly-used BPS tools, such as EnergyPlus and TRNSYS, act solely upon deterministic sets of input data, disregarding the associated uncertainties [4]. Solving optimization problems in the field of performance-driven building design with deterministic approaches oversimplifies reality and leads to overestimation or underestimation of building performance [5].

Using deterministic methods in the process of building design decision-making fails to respond to different attitudes towards risks and uncertainties in the process of building design. The following questions often emerge after conducting a conventional design optimization, but deterministic methods fail to answer: Given a Pareto optimal set,

which is a set of the best design options resulting from a building design optimization process, what criterion is the most significant in selecting the final best option? How would probability distributions of design input parameters affect the output distributions and the results of design decision-making? Is it more important to achieve a performance target with a maximum expected value (within the Pareto optimal or elite set), or to take risks for achieving the best possible performance (with a smaller probability)? For instance, in the field of health care facilities design, maintaining the thermal comfort of patients is a critical design objective and may not be compromised for getting a higher energy saving. A design option which provides thermal comfort for sure could be more preferred than a design option with a 50% chance of maintaining thermal comfort with achieving a higher energy saving. However, this preference order may be reversed in a storage facility design project.

The uncertainties play a significant role in performance assessment of building design alternatives and ultimately, the result of design decision-making [6]. Compared with the existing deterministic methods for architectural design, using probabilistic methods may result in significantly different design decision to be made, or different design options to be selected, which is to be investigated and demonstrated in this dissertation.

The probabilistic methods provide the required information for a more detailed evaluation of competing design alternatives. However, despite the noticeable benefits of previous studies and existing tools to use probabilistic methods for building design decision-making process, an integrated framework to guide designers in using the

probabilistic methods is missing. There is a lack of a proper connection between common design tools and probabilistic methods. The capabilities of parametric design and BIM tools have not been fully explored to apply probabilistic methods in performance-driven building design decision-making.

The investigation of limitations and challenges of deterministic methods for performance-driven building design decision-making has urged conducting this research. This research addresses the problems or challenges associated with conventional methods of performance-driven building design optimization, i.e., ignoring the existing uncertainties and lacking a systematic framework to incorporate probability and risk assessment in building performance predictions. These deficiencies necessitate the development of a new approach to probabilistic building design optimization using more user-friendly and information-rich software, i.e., parametric design tools and BIM.

This study addresses the abovementioned challenges related to performance-driven building design optimization by answering the specific research questions as follows:

1. What are the challenges in the current performance-driven building design optimization, specifically building energy performance, to be addressed by statistical methods?
2. How do the probability distributions of design input parameters made into BIM building design tools affect building performance optimization and design decision-making?

3. How can we incorporate uncertainties in outcomes in selecting and formulating improved design options?

## **1.2 Research Goal, Objectives, and Limitations**

The main goal of this research is to develop a framework to handle uncertainties and risks involved in the process of performance-driven building design optimization and decision-making using parametric BIM. This framework takes advantage of findings from the fields of engineering and management to support performance-driven building design decision-making, facilitating the access to probability distributions of design inputs and simulation outcomes.

The following specific objectives are defined to achieve the main goal of this research:

1. To specify existing uncertainties in the current building design decision-making, specifically building energy performance, that can be addressed by statistical methods.
2. To determine the potential statistical means to address the challenges found in the literature and develop a probabilistic framework to incorporate uncertainties in outcomes in selecting and formulating “optimal” design options.
3. To add parameter distributions to BIM authoring tools.
4. To develop and validate multiple test cases to demonstrate the usability of the proposed framework.

This research has studied some sources of uncertainties in building energy performance assessment, with three test cases. Furthermore, two types of probability distributions including the normal and the Poisson distributions are used as example distributions of input parameters in this research. Other probability distribution types could be studied in the future.

### **1.3 Research Strategy**

This section introduces the overall research strategy used to address the research questions and validate the findings.

#### **1.3.1 Methods**

This work requires a set of skills and knowledge in parametric building design and building performance analysis along with statistical analysis and computer programming, which were obtained through academic training and resources. This study has been done through three major steps as follows:

1. Literature review to analyze the current state in building performance analysis and identify current challenges regarding uncertainties and potential solutions. Literature review was conducted to identify the applications of uncertainty analysis in building performance simulation and optimization. The application of statistical methods and measures are studied which may lead to different design options to be selected, compared to conventional deterministic design methods. Furthermore, different sources were reviewed to understand design parameter definitions in BIM tools and the ways to access parameter definitions and add probability distributions in BIM.

2. A framework was developed based on the outcome of the literature review to use parameter distributions made into BIM in order to improve the result of design decision-making. This framework uses the distributions of simulation outcomes to enhance the process of building performance prediction, design alternative selection, and design optimization under uncertainties.

3. The proposed framework was tested and validated with three experiments and prototypes. The experiments and prototypes developed are for the use in this research, but they have the potential to be used by other researchers and future end users.

### **1.3.2 Tools and Data**

Adding probability distributions of design input parameters using BIM API and computer programming is implemented to support building performance prediction based on probabilities and provide a more robust basis for building design decision-making. Autodesk Revit is a BIM software intended to allow architects and other building professionals to design and document a building [7]. The generated data is used in Grasshopper to run energy simulation using Ladybug Tools. Grasshopper is a visual programming environment that runs in the Rhinoceros. Ladybug Tools is an environmental design software package that connects Grasshopper environment to validated simulation engines including EnergyPlus. The energy simulations results are exported to Microsoft Excel, and JMP is used to visualize the data and analyze the outputs. JMP is a suite of computer programs for statistical analysis developed by the JMP business unit of SAS Institute [8].

## 1.4 Contributions to the Field

This research makes multiple contributions to the field of performance-driven building design decision-making:

- A novel integrated framework is created for integrating BIM into probabilistic building energy simulation to enhance user interface and system interface for such simulation. This step includes:

1. Creating a plugin to add probability distributions of design input parameters in BIM.

2. Developing a data inventory including the probability distributions of thermal properties of building materials, based on the findings from the existing literature.

3. Creating a parametric platform to run probabilistic energy simulations.

4. Creating a post-processing platform to compare deterministic results with probabilistic results, and applying different decision-making criteria to enable designers to consider different attitudes towards risk in design decision-making.

- Different performance rankings of design options are found in one test case when comparing deterministic and probabilistic methods. In addition, different test cases led to different conclusions about such rankings, which demonstrates the significant impact of probabilistic methods on design decision making.



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## **1.5 Significance**

This research has addressed the problems and challenges associated with conventional methods of performance-driven building design optimization, i.e., ignoring the existing uncertainties and lacking a systematic framework to incorporate probability and risk assessment in building performance predictions.

The framework developed in this research allows the evaluation of design options based on not only their predicted performance but also the probability of their occurrence. The proposed framework will contribute to the process of performance-driven building design by:

- handling uncertainties associated with building design and simulation models and provide more reliable predictions on building performance, through uncertainty analysis.
- evaluation of competing design alternatives using probabilistic methods. Integrating probabilistic measures with different decision-making criteria including expected value, maximax, and maximin, considering risk attitudes, for making well-informed design decisions.

## **1.6 Outline of the Chapters**

This research is comprised of seven chapters.

CHAPTER 1 INTRODUCTION provides an overview of this research including the detailed background, research problem, objectives, strategy, contribution, and significance.

CHAPTER 2 LITERATURE REVIEW reports a thorough literature review to identify uncertainty sources, uncertainty analysis and risk assessment methods and applications in performance-driven building design decision-making under uncertainties, and the integration of Building Information Modeling, parametric design, and simulation tools in this process.

CHAPTER 3 METHODOLOGY introduces and describes the methods of this research.

CHAPTER 4 PROTOTYPE DEVELOPMENT describes the workflow of using BIM, parametric modeling, simulation, and statistical analysis tools for the probabilistic building performance simulation and design decision-making.

CHAPTER 5 TEST CASES presents test cases to validate the usability of the new framework for performance-driven building design decision-making under uncertainties.

CHAPTER 6 RESULTS AND DISCUSSION presents the results and discussions of the three experiments.

CHAPTER 7 CONCLUSION concludes the process, results, and findings of this research and proposes future research opportunities.

## CHAPTER 2

### LITERATURE REVIEW

This chapter reviews the existing literature to identify the research gaps and the agenda for this study. This chapter is divided into three major sections, introducing building performance analysis methods and the associated uncertainties, uncertainty analysis methods and the applications in building design decision-making, and the integration of Building Information Modeling (BIM) and parametric design tools into the probabilistic design decision-making.

Section 2.1 *Building performance analysis* introduces existing building performance simulation tools and the major sources of uncertainties in the field of performance-driven building design. Section 2.2 *Probabilistic risk assessment for building energy performance simulations* introduces uncertainty analysis and risk assessment methods for building design decision-making. Section 2.3 *BIM and parametric tools* discusses the capabilities of BIM and parametric analysis tools in performance-based building design decision-making under uncertainties.

#### **2.1 Building performance analysis**

Architectural design decision-making begins with identifying design problems and objectives. It sets boundaries for designers' potential problem-solving methods. Performance-based building design focuses on methods and strategies that integrate and optimize different aspects of building performance. Using the computer power allows

designers to explore a broader range of solutions, efficiently. Building Performance Simulation (BPS) tools have been extensively used by the architects and engineers to simulate building performance. The BPS tools facilitate the estimation of quantifiable building performance criteria prior to construction.

The BPS tools usually consist of three parts: input variables, calculative models, and model output [9]. A calculative model produces building performance predictions (model output) based on a set of input data including physical characteristics, interior conditions, weather data, and mechanical specifications [10], [11]. The majority of these input variables are subjected to significant alterations during the construction process or even later as a building is at use [9].

The level of reliability and effectiveness of a BPS tool depends upon the accuracy of input and transparency of the calculative model. The Building Energy Software Tools Directory provides an ongoing list of 179 simulation tools [12], but most of these tools are not designed to deal with uncertainties. The majority of the BPS tools only collect deterministic input data and run a single deterministic simulation for each design alternative [3], [13]; thus, the outputs are not immune to uncertainties.

### **2.1.1 Model-based building energy simulation**

A lot of energy models deploy either physical (white-box) approaches or empirical (black-box) techniques to simulate building energy performance. At one extreme, BPS tools implementing physics-based models, e.g., EnergyPlus, require a large number of

input variables, thus may be extremely time intensive [14]. At the other extreme, some empirical models such as Artificial Neural Network need a significant amount of training data and can be computationally expensive [15]. In the middle of this range, there are hybrid or grey-box models that do not require as many input details as physics-based models nor as long of a training process as empirical models.

The most popular hybrid model in the field of building energy analysis is known as Resistance and Capacitance (RC) [16]. In this model, building thermal model is replaced with an electrical model including separated nodes, assuming all the building parameters are time invariant [17]. This method facilitates modeling the temperature in state-space form and allows the estimation of actual time-varying thermal behavior of building [18]. Due to its advantages, the use of RC models has been reported in many building energy assessment studies. Thermal load analysis is one of the main applications of RC models in building energy analysis. Also, the adoption of RC models in building parameter estimation, accompanied by different data collection and optimization methods has been reported in a number of studies.

McKinley and Alleyne [19] created an RC model to estimate thermal properties of building elements and minimize inside solar and occupant loads. An optimization algorithm based on the interior-reflective Newton method (available in MATLAB optimization toolbox) was deployed for parameter estimation. Building simulation is combined with the on-site measurements to estimate the unknown design parameters. Bengea et al. [17] applied the RC network analogy in a parameter estimation process to

determine the effects of sensor measurement errors and load uncertainties on building control closed-loop performance. For parameter estimation, the Least Square algorithm was applied, and Monte Carlo simulations were conducted to evaluate the quality of parameter estimation. Jimenez et al. [20] applied the RC modeling in parameter estimation of building material thermal properties. They used IDENT toolbox (Graphical User Interface of MATLAB System Identification) coupled with properly defined physical constraints [20].

Physics-based models, especially EnergyPlus and ESP-r, are widely applied in uncertainty analysis for building performance analysis. EnergyPlus is the most popular energy analysis tool used in uncertainty analysis studies [3] since the Input Data File (IDF) is editable with programming languages [21]. Also, Esp-r has a specific package for uncertainty analysis which facilitates computing many simulations required for uncertainty analysis [22].

This research deploys an RC model for developing the initial probabilistic framework. EnergyPlus, OpenStudio, 3D model tool Rhino, and its visual programming environment Grasshopper are used for the advanced framework.

### **2.1.2 Existing uncertainties in building performance analysis**

A generic representation of the building model, including the geometry, layout, and orientation, is provided through conceptual and schematic stages of building design [23]. The early stages of design introduce a great potential to improve building

performance at a lower cost, although many design parameters are still undecided and subject to change [24]. Research shows that the building design process is not immune to uncertainties even in later stages of design [25]. In later stages of building design, i.e., design development, design input parameters are determined but might not be consistent with the actual building after construction. For instance, the thermal properties of building elements are consistently deteriorating due to the effects of temperature variations and humidity. Also, unexpected climate changes, and complex user behavior may deviate from the initial estimations and significantly impact the architectural, structural, or facility design, since a slight change in the building properties may affect heating/cooling loads, thus altering the size of ductwork and building structure weight [22].

Two types of uncertainties in building performance analysis are known as aleatory and epistemic uncertainties [25]. The aleatoric term refers to parameters that are essentially unpredictable and dependent on other factors, e.g., occupant behavior or discrepancies between expected and actual plant system efficiency [26]. Another example of aleatoric uncertainties is the measurement errors and inaccurate coefficients of simplified simulation models. This type of uncertainty exists due to computational and numerical imperfections and is also referred to as random errors [22]. These uncertainties cannot be reduced by designers but can be quantified using probabilistic methods.

On the other hand, the epistemic uncertainties are the unknown parameters that exist in all stages of design due to a lack of adequate knowledge. For instance, the actual quantity of internal heat gain from lighting and equipment or the thermal properties of

building materials may be different from design assumptions or change during the building operation [3]. This type of uncertainty is also known as systematic errors [22]. The epistemic uncertainties can be quantified with probabilistic or non-probabilistic methods and their effect on the building performance is reducible [3].

Among all categories of uncertainties, the critical sources of uncertainties in building performance analysis are known as (1) weather data, (2) occupant behavior, (3) HVAC performance, and (4) installed thermal properties of building envelope materials [3].

Weather condition is constantly changing, and climate change is expected to affect the thermal behavior of buildings dramatically in the future [27]. The probabilistic methods have proven to be useful to conduct more rigorous energy analysis considering this type of uncertainties. Tian & de Wilde [28] discussed the integration of probabilistic techniques with EnergyPlus for building performance predictions under climate change in the long-term future. They applied three probabilistic methods including statistical reduction, simplification using degree-day theory, and metamodels. Tian & de Wilde [28] found that the first method provides the most accurate results, while a combination of the second and the third methods is less computationally demanding. Tian & de Wilde [28] deployed a probabilistic sensitivity analysis technique integrated with building simulation tools to identify efficient design assumptions and critical design parameters. They proved that this process would allow predicting the effects of climate change on the future performance of buildings and improve the building adaptability over a long time.



Complex occupant behavior is another major source of uncertainties causing about 30% of the variations in building energy performance [29]. O’Neill & Niu [30] studied the impact of occupant temporal behavior, e.g., the occupant presence duration and arrive/leave time, on building energy performance. They integrated EnergyPlus with a schedule-based behavior model for uncertainty and sensitivity analyses and showed that this factor would impact the HVAC annual and peak energy consumption up to 4% [30]. Bae [31] studied the impact of uncertainties related to occupant behavior on building energy optimization through the application of EnergyPlus connected to a Genetic Algorithm that used a probabilistic search technique based on evolutionary principles.

HVAC specifications are varying over time due to oversizing, aging, and maintenance. These variations add to the uncertainties in building energy performance analysis. Wang [32] studied the impact of the HVAC uncertainties on building energy analysis, with integrating EnergyPlus and Georgia Tech Uncertainty and Risk Analysis-workbench (GURA-W). This research [32] used a classical statistical method, “Probability Integral Transform” to estimate the magnitude of the HVAC operation uncertainties. Sun et al. [4] studied the effects of uncertainties in the actual heating/cooling demands on HVAC operation and proposed the application of uncertainty and sensitivity analyses for HVAC system sizing, to provide a range of possible design solutions and deal with different attitudes towards risk among different building owners.

Degradation of building physical elements over time affects the thermal properties of the building material, e.g., thermal conductivity, density, and specific heat capacity.

These changes add to the uncertainties in building energy performance analysis. The works of Hopfe [25], MacDonald [22], and Prada et al. [33] are among many others who studied the uncertainties associated with the thermal properties of building materials and proposed effective methods using Monte Carlo simulations to handle building energy assessment. Hopfe [25] integrated a decision-making protocol, analytical hierarchy processing (AHP), with uncertainty and sensitivity analyses, and concluded that including uncertainties in BPS tools is important. MacDonald [22] studied the internal and external approaches in quantifying the impact of uncertainties on building performance simulation results at the early and detailed design stages. Prada et al. [33] specifically studied the effects of uncertainties in thermal properties of building materials on the energy transfer of building envelopes.

## **2.2 Probabilistic risk assessment for building energy performance simulations**

Building design decision-making under uncertainty is one of the main challenges in performance-based building design [2], [34]–[36]. Solving this type of design problem with deterministic approaches may lead to overestimation or underestimation of design requirements [26]. On the other hand, research shows that non-deterministic methods including variance-based probabilistic methods can improve the efficiency of building design decision-making under uncertainties [6].

Deterministic methods in performance-driven building design decision-making fail to address existing uncertainties in design decision-making. Uncertainty analysis

techniques such as Monte Carlo coupled with risk assessment methods introduce a potential solution to tackle uncertainties and make robust design decisions.

### **2.2.1 Uncertainty analysis methods and applications**

Applicable Uncertainty Analysis (UA) methods in the field of building energy analysis are categorized into two groups of forward and inverse approaches [3]. Currently, forward UA methods are more common in building energy assessment, although new approaches to inverse UA are growing [24].

Forward UA strategies, also known as uncertainty propagation analysis, apply mathematical models to quantify the variations of the model output caused by uncertainties in the input variables. Among all forward UA methods, Monte Carlo approaches are the most popular, since they apply to most of the simulation environments, also deal with different types of probability distributions denoting input variables [3]. The Monte Carlo approach does not require to rewrite the theoretical equations and is more intuitive and easier to implement [9].

Inverse uncertainty analysis, also referred to as model calibration, allows determining unknown input variables through mathematical models based on the available output data. Rezaee et al. [37] studied inverse uncertainty analysis methods to improve the efficiency of decision-making in the early stages of building design. Bordbari et al. [38] used two-point estimate method (2PEM) to estimate uncertain input variables, including

heating, ventilation, and air conditioning (HVAC) system configuration, building structure, and interior conditions description.

### *Monte Carlo uncertainty analysis*

The Monte Carlo simulations use random variables and input probability distribution functions to address the stochastic status of the problem. The following is a brief mathematical description of the Monte Carlo method for dealing with input uncertainties and uncertainty analysis.

Let a mathematical modeling  $Y = f(x)$  define correlations between a vector of input variables  $X = \{x_1, x_2, \dots, x_k\}$  and an output  $Y$ , where  $f$  is a deterministic integrable function which translates from a  $k - D$  space into a  $1 - D$  one, i.e.,  $\mathbb{R}^k \rightarrow \mathbb{R}$ . The model produces a single scalar output  $Y$  when all input variables are deterministic scalars. However, if some inputs are uncertain, the output  $Y$  will also associate with some uncertainties. An input variable  $x_i$ , is defined by a mean value  $\mu_i$ , a variance  $\sigma_i^2$ , and a probability distribution, such as normal, uniform, Poisson, etc. In the Monte Carlo methods,  $N$  sets of samples from possible values of each input variable are generated. These input values are inserted into the simulation model to generate the probability distribution of the output  $Y$ . Processing the output range  $Y$  delivers the frequency distribution of the output with mean value, standard deviation, variance, etc.

The challenge of mapping between simulation tools and probabilistic techniques in the process of Monte Carlo simulations has received a lot of attention in the literature.

The programming languages such as MATLAB [13], Python [39], Excel’s Visual Basic Application (VBA) [40], and R environment [37] are used to automate sample generation and executing the simulation model repeatedly. Table 1 lists some of the previous studies using the Monte Carlo method for building performance analysis.

**Table 2-1 An overview of the literature in the application of Monte Carlo in building performance analysis.**

<b>Ref.</b>	<b>Building Type</b>	<b>Focus</b>	<b>Tools</b>	<b>Sampling Methods</b>	<b>Uncertainty Type</b>
[13]	An office room	Building energy consumption and thermal occupant comfort	MATLAB, VA114	LHS	Building materials, internal heat gains, WWR, infiltration rate, room size,
[41]	A well-controlled conditions within outdoor test cells	Building energy performance	Esp-r	Monte Carlo (Random)	Building materials, scheduled operations
[42]	A 4-story office building	Thermal occupant comfort and investment cost	ESP-r and BFEP	LHS	Wind pressure, indoor air temperature distribution,
[37]	A modular classroom	Building energy performance	R programming language, ModelCenter	Markov Chain Monte Carlo	Building materials, WWR, internal heat gains, Building height, air leakage
[43]	An office building	Cooling loads of district cooling systems	EPC	LHS	Outdoor weather, building length, WWR, building materials, internal heat

					gains, ventilation rates
[39]	A 2-story office building	Building energy performance	eQUEST and DOE-2	Monte Carlo (Random)	Building materials, building shape, occupant schedule
[40]	an air-conditioned university building	Thermal performance of buildings	EnergyPlus	LHS	Climate conditions, building materials, internal heat gains

Hopfe et al. [13] studied uncertainty analysis in an office building energy consumption and thermal comfort assessment through connecting MATLAB with a building performance simulation tool, called VA114. They declared that including uncertainties in building performance analysis could support the process of building design decision-making. Macdonald and Strachan [41] integrated uncertainty analysis with building energy simulation using Esp-r software. They studied the uncertainties in thermal properties of building materials and building operation schedules and concluded that uncertainty analysis facilitates risk assessment and improves building design decision-making. de Wit and Augenbroe [42] studied the impact of variations in building material thermal properties, along with model simplifications, on building thermal behavior, using two simulation tools, ESP-r and BFEP, integrated with Monte Carlo uncertainty analysis technique. Rezaee et al. [37] studied inverse uncertainty analysis methods to improve design decision-making models. They applied linear inverse modeling to generate probability distributions for design inputs, given a preferred energy performance. Gang et al. [43] developed an optimization method to include uncertainties

in cooling loads calculations and designing of district cooling systems. They concluded that the integration of uncertainty analysis in the design process enables designers to evaluate the performance of district cooling systems with quantifiable confidences and based on the risk and benefit analysis. Asadi et al. [39] used Python programming to automate the integration of Monte Carlo simulations into energy analysis. They developed a regression model as a pre-diagnostic tool for energy performance assessment of office buildings to identify the influence of each design input variable. Tian and de Wilde [40] presented a generic methodology for running a probabilistic building energy performance analysis in a long term future. They demonstrated the application of the proposed method to a building thermal performance analysis, including the uncertainties associated with weather conditions and building internal heat gains.

Despite the noticeable benefits of the previous studies and existing tools to conduct uncertainty analysis, an integrated framework to use the probabilistic methods in performance-based building design decision-making using Building Information Modeling (BIM) and parametric tools is missing. Table 2-2 defines the requirements of this integrated framework and reviews the previous efforts explicitly with respect to those requirements.

**Table 2-2 Research gap identification**

	<b>MacDonald &amp; Strachan 2001</b>	<b>De Wit &amp; Augenbroe 2002</b>	<b>Hopfe &amp; Hensen 2011</b>	<b>Kim et al. 2011</b>	<b>Tian &amp; de Wilde 2011</b>	<b>Lee et al. 2013</b>	<b>Asadi et al. 2014</b>	<b>Gang et al. 2016</b>	<b>Pruvost &amp; Scherer 2017</b>	<b>Rezace et al. 2018</b>
<b>Using BIM and Parametric tools</b>	x	x	x	Δ	x	x	x	x	Δ	Δ
<b>Using a data inventory with multiple probability distributions</b>	x (n)	x (n)	x (n)	x (n)	x (n)	√	x (u)	√	-	√
<b>Comparison of deterministic and probabilistic</b>	x	x	x	√	x	√	x	√	x	x
<b>Statistical Post-processing</b>	√	√	√	√	√	√	√	√	√	√
<b>Uncertainty analysis for risk assessment</b>	x	√	x	x	x	x	x	x	√	x



x: does not address                      (n): Normal distribution only  
Δ: partially addresses                    (u): Uniform distribution only  
√: addresses

This research addresses this challenge with developing an integrated probabilistic framework for building energy analysis, using the BIM platform and parametric design and simulation tools. The implications of the framework on choosing the best design options are expected to enhance design decision-making.

### **2.2.2 Input probability distributions**

Building design input variables can be categorized in two groups of discrete and continuous random variables. A variable is discrete if its observations can only take a countable number. On the other hand, if observations of a variable can take any uncountable number in an interval, the variable is known as a continuous variable [44].

For modeling uncertainties of discrete variables in building design and simulations, the Poisson probability distribution may be used. On the other hand, the uncertainties of continuous variables in the building performance simulations are usually modeled using normal probability distribution [44].

#### *Poisson probability distribution*

The probability distribution of a variable is Poisson if the following conditions are met [44]:

1. Only one event occurs at a time or a space, not two or multiple events.
2. The occurrence of an event in a specific time period or space is independent of the occurrence of other events in other time frames or spaces.
3. The average event rate in any period of time or space,  $\lambda$ , is the same as the average event rate in any other period or region.

A Poisson distribution is a discrete probability distribution for a random variable. This probability distribution represents the frequency of an event happening over a unit of time or space. In this probability distribution, the average number of events in an interval, or the event rate ( $\lambda$ ) is known by the experimenter and is assumed to be fixed. The event rate is independent of any occurrences, also the occurrence of one event does not have an impact on the next event, in other words, the events are occurring independently.

For a discrete random variable  $x$  with a Poisson distribution, the probability mass function (PMF) of  $x$  is defined by:

$$P(k \text{ events in interval}) = e^{-\lambda} \frac{(\lambda)^k}{k!}$$

where, parameter  $\lambda$  (the average event rate) is greater than 0,  $k$  (the number of times an event happens in an interval) = 0, 1, 2, ..., and  $e$  is Euler's number ( $e = 2.71828\dots$ ).

A Poisson distribution can be applied to the variables with a large number of possible events, but the chance of occurrence for each event is rare.

#### *Normal probability distribution*

A normal or Gaussian distribution is a continuous probability distribution for a random variable. If  $x$  represents the random variable, then the height of the relative frequency histogram for a specific value of  $x$  is represented by  $f(x)$  and the general form of its probability density function is:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

where  $\mu$  is the mean or expectation of the population of  $x$ -values, and parameter  $\sigma$  is its standard deviation [44]. The normal probability distribution is bell-shaped and symmetrical around the mean value,  $\mu$ .

#### *Input variable sampling*

Uncertainty analysis with Monte Carlo simulations requires to execute the model simulation repeatedly using many samples of the input variables. There are various sampling methods introduced in the literature, including random (Monte Carlo), stratified, factorial, Latin Hypercube, and quasi-random [45]. The applicability of these methods depends on the type of an analysis and characteristics and limitations of an experiment [46].

The three most common sampling methods in the fields of building energy analysis are known as random (also called Monte Carlo), Latin Hypercube Sampling (LHS), and quasi-random sampling [3]. Kucherenko et al. [47] compared these sampling methods in terms of efficiency and concluded that LHS is a more efficient sampling method and is recommended due to its capability in converging simulation results with fewer samples, compared to random and quasi-random sampling methods.

The random sampling method selects random samples from the probability distribution of input parameters. This method requires many more samples for convergence compared to the other two methods, although the mean and variance values found for the simulation output is more accurate than other sampling methods [48]. Lu et al. [49] used random sampling to implement uncertainty and sensitivity analyses and study the electricity and gas consumptions of four types of buildings in Ma'anshan city in China. They compared the results with that obtained from the conventional deterministic method and found that there was 16.6% difference in the results of the two methods. Asadi et al. [50] applied random sampling method to generate ten thousand building configurations for seven building shapes and run energy simulations using eQUEST and DOE-2. They studied building materials, shapes, also occupant schedules as design input variables and then collected the results of energy simulations to implement uncertainty analysis and predict building energy consumption using regression equations.

The LHS method divides the range of an input variable into segments (hypercubes) and selects samples from each segment until all segments have equal number of samples.

This sampling method has been broadly applied in the field of building performance analysis including the works done by [51]–[53]. Kim and Park [51] applied the LHS method in an experiment to conduct a robust multi-criteria optimization and select the optimal double glazing system for an office building. Their design objectives were maximizing thermal comfort and minimizing building energy consumption. Ascione et al. [52] used the LHS method integrated with EnergyPlus and MATLAB to perform sensitivity analysis and conduct a robust energy analysis for a hospital building. Kim et al. [53] adopted the LHS method for sampling and conducted a multi criteria decision-making for HVAC system selection in a library building. Their design objectives were construction cost and total energy consumption.

The quasi-random sampling obtains faster convergence rate than the random sampling method. This means that fewer simulations are needed to obtain the same statistical accuracy, thus this method can handle large number of input variables at the same time [54]. Sobol sequence is an example of quasi-random sampling method that selects samples from a user-defined probability distribution randomly and evenly. This method is an efficient space-filling technique that uses a base of two to form smaller unit intervals and filling them uniformly. Eisenhower et al. [10] applied quasi-random sampling to study the effects of 1000 input variables in a building energy analysis. This research uses the LHS method for the variables with normal probability distribution and the random method for those with Poisson probability distribution.

### 2.2.3 Risk

The international ISO standard (ISO 31000:2009) defines “risk” as the effect of “uncertainty” on objectives, that could be positive consequences as well as negative impacts [55]. Many risk analysis methods have been established. Pruvost and Scherer [56] list some of the most common risk analysis methods in the fields of engineering, management, and finance:

- probability-impact matrix,
- fault trees,
- Failure Mode and Effect Analysis (FMEA),
- influence diagrams,
- neural networks, and
- uncertainty analysis based on Monte Carlo or Latin Hypercube sampling.

Learning from the fields of finance and management, the uncertainty analysis method seems promising to be applied in the field of building energy analysis and design decision-making. This approach concentrates more on the deviations in targeted objectives and less on exploring all the problems associated with an action. In this approach, two major terms are introduced:

- Key Performance Indicators (KPI) [57], and
- Key Risk Indicators (KRI) [58].

While KPI is a metric to measure the performance or objective, KRI measures deviations from the target and depicts the threat of breaching a specific threshold [56]. KPI and KRI are useful metrics to measure the objective aspect of risk (likelihood), also facilitate decision-making based on the risk attitude of decision makers and evaluate the performance subjectively.

A building energy model is too complex, and it is difficult to estimate the variance of the output by just reviewing the variance of the input parameters. In building energy projects, KPI could be defined as building annual energy consumption or energy saving, and KRI may show the possibility of occurrence of discrepancy between expected energy performance during the design stage and real energy performance after project completion [59]. Thus, performing a probabilistic analysis and uncertainty propagation for identifying the probability distribution of the output could be helpful in the process of risk assessment and design decision-making.

#### **2.2.4 Design decision-making under uncertainties**

A significant question in building performance analysis and design decision-making is how to handle the existing uncertainties. Haymaker et al. [60] reported the development of a computational performance-based design method using Perkins and Will's Design Space Construction (DSC) performance-based computational framework (Perkins and Will is a global architecture firm founded in 1935). They tested their proposed method in a mixed-use high-rise building design in Seattle, WA. Haymaker et al. [60] identified a need for including uncertainties in building design space construction

and decision-making in a way that design teams can incorporate the added complexity into their decision-making process. In another study, Hopfe and Hensen [13] state that considering the uncertainties in building performance analysis provides the design decision makers with an evidence-based decision support. Østergård et al. [61] declare that comparing different design options under uncertainty is challenging and requires further research and development. They suggested using histograms and statistics to compare the output distributions for different design options.

Uusitalo et al. [62] argued that the uncertainties associated with the outcome of deterministic models need to be estimated in order to be most useful in the process of design decision-making. They listed some practical approaches to estimate the uncertainties related to the deterministic models, including expert assessment, model emulation, and model uncertainty analysis.

The expert assessment is a well-known method to estimate the uncertainties of models that are too expensive or impossible to observe directly. This method was used by [63], [64]. However, the main questions in this using this approach are “which expert to choose?” and how to combine the estimations obtained from multiple experts [62]. [63], [65] have proposed some strategies for interviewing the experts and combining their estimates.

Recently, model emulation has been applied in some research to estimate the uncertainties associated with more complex models. Using this approach, a simpler substitution of the original complicated model is created, and the uncertainties associated



with the emulator are quantified [62]. This method can be most useful, when the emulator is created with sufficient accuracy [66].

The model uncertainty analysis using the Monte Carlo method is known as the most comprehensive technique to obtain the probability distribution of the model output [67]. This technique examines the probable range of the output based on the probability distributions of the inputs. The key challenge of this method is requiring a high number of samples and model runs [62]. Rezaee et al. [68] proposed a design decision-making approach based on the level of confidence for the fact that the selected design option would be performing better than the other options. Rezaee [24] recommended further research to create a bridge between BIM tools including Revit and statistical computational tools. The current research proposes the application of BIM and parametric design tools with the EnergyPlus simulation engine to create this bridge, obtain the probability distributions of input variables, generate the samples, and automate the energy simulation runs.

The uncertainty analysis with Monte Carlo requires a decent knowledge about the probability distribution of the input variables, in order to generate samples and run the model multiple times. Lee et al. [69] introduced an uncertainty analysis toolkit explicitly for building performance analysis referred to as the (Georgia Tech Uncertainty and Risk Analysis Workbench) GURA\_W. The identification and modification of input variables are possible using GURA\_W, and the uncertainty quantification repository available in this tool allows the users to access the uncertainty distributions of previous parameters being modeled. However, this tool is not accessible to the public, yet. The current research

did not have access to this database and referred to other available literature to create the probability distributions of the input variables.

Different decision-making criteria including expected value, expected opportunity loss, maximax, maximin, Laplace, Hurwicz, and minimax are proposed in the literature for handling the inevitable uncertainties in building performance analysis [31]. de Wit and Augenbroe [42] applied expected value and expected utility decision-making criterion to discuss how designers can use the extra information obtained from uncertainty analysis to make more informed design decisions.

The criteria of expected value, maximax, and maximin for risk assessment and design decision-making under uncertainties are applied in this research.

#### *Expected value criterion*

The Expected Value (EV) of a variable is the return expected or the average benefit gained from that variable. This statistical measure, the sum of all possible gains, each multiplied by their probability of occurrence, demonstrates the cost-benefit analysis of a design alternative, considering the input uncertainties. The EV for a design alternative (X) is the sum of all possible outcomes of X weighted by the probability of each outcome [70]. Equation 1 shows the formula to calculate the EV of design alternative j [71]:

$$EV_j = \sum_{i=1}^n p_{ij}c_i$$

where  $p_{ij}$  is the probability of outcome  $i$ , given design alternative  $j$ , and  $c_i$  is the value of the consequence of outcome  $i$ , assuming a total of  $n$  outcomes.

de Wit and Augenbroe [42] applied the criterion of EV to evaluate competing decision alternatives. Their example describes a situation where a designer needs to make a decision on whether or not to use a cooling system in their building design. The designer would decide to use a cooling system only if the indoor temperature excess of the building without a cooling system is more than 150 hours. Based on their probabilistic results, they concluded that the most likely value of the outcome would be well below 150 hours and the designer could make their decision comfortably not to include the cooling system in their design.

#### *Maximax and maximin criteria*

However, design alternatives are not always assessed objectively, as suggested by the EV theory. It is important to know how likely different design outcomes are to occur for a design alternative, but decision-makers' preferences affect their decision in selecting the optimal design option as well [70]. The best choice for one design decision-maker might not be the best for another one with different preferences. It is not always the best decision to select the design alternative with the maximum EV. There may be a situation which demands risk-averse decision-making and selecting a design alternative which can go the least wrong. This decision-making strategy is known as maximin and suggests selecting the design alternative with the best worst-case scenario [31], [72]. On the other hand, taking a different approach towards risk might lead to selecting a design option with

the most optimistic possible outcome. This decision-making strategy is termed maximax and is useful in risk-seeking design situations [31], [73].

### **2.3 BIM and parametric tools**

BIM supports data interoperability in the process of building performance analysis. This data may include building performance metrics, construction time, cost, etc. Building Information Modeling (BIM) is a developed technology with object-oriented programming capabilities which has proven to be helpful in the field of building design and performance analysis [74]. Dynamo, a visual programming user interface working with Revit, allows extracting model information from Revit, thus solves the challenges of data transfer between Revit and energy simulation tools, while preserving and enhancing the parametric change capability of the BIM models. Such data as geometrical information, quantities, properties of building elements, and cost estimates can be exported to analysis tools [52], [53]. Furthermore, BIM API programs and computer programming enable users to access the BIM data and adding to it using available classes [77].

Parametric modeling and simulation platforms, e.g., Dynamo and Grasshopper facilitate the iteration of performance analyses and optimizations in architectural design. Asl et al. [76] used Dynamo as an open-source visual programming user interface linked with Revit, to generate building design alternatives, assess the performance of the design options, and search for the optimal solutions. Wortmann [78] used the Grasshopper

platform to create and test a model-based optimization plugin, Opossum, for performance-based building design.

### **2.3.1 BIM API development**

Revit Application Programming Interface (API) is an Autodesk product that allows two applications such as Visual Studio and Autodesk Revit to communicate. Users can apply Revit API with any .NET compliant languages including Visual Basic.NET, C#, and C++/CLI to program for modeling automation, data collection, simulation, etc. [79].

Jeong et al. [80] used the Revit API to connect Autodesk Revit and Modelica, which is an object-oriented equation-based simulation environment, to translate building architectural model to building energy models. The authors conducted three different test cases to demonstrate and validate the proposed approach. In another research project, Yan et al. [74] applied the Revit API to translate Revit architectural models to energy models in Modelica for energy simulations, and create input files for daylight simulations in Radiance, which is a ray-tracing software for building daylight analysis. The authors created two prototypes to build the connection between Revit and simulation tools including Modelica and Radiance.

### **2.3.2 BIM integrated with uncertainty analysis and risk assessment**

BIM technologies may be useful in performance analysis and risk management since they facilitate transferring data from BIM authoring tools to other analysis tools, also enable designers to automate iterations in design and analysis processes [81], [82]. Kim et

al. [83] applied the Monte Carlo uncertainty analysis in building energy analysis through the integration of BIM and MATLAB platforms. A set of software applications including Revit Architecture 2010, ECOTECH 2010, and EnergyPlus 6.0 were used for modeling and simulation. For uncertainty analysis, the MATLAB Graphical User Interface (GUI) platform was applied to develop a self-activating Monte Carlo simulation program. Rezaee et al. [68] provided a CAD-based inverse uncertainty analysis tool to estimate the unknown input parameters and improve design decision-makers confidence in the early stage of building design. They created two energy models, one in EnergyPlus and another one in a spreadsheet-based energy analysis tool to run the energy calculations.

Although BIM and parametric design and optimization tools allow the iteration of building performance simulations, the integration of Monte Carlo into the platform of these applications have not been broadly studied. For the performance-based building design, further studies are required to provide clear guidance on the mapping between BIM authoring tools, parametric analysis tools, and probabilistic techniques such as Monte Carlo to provide probabilistic outcomes for building energy analysis [81]. This research intends to apply variance-based methods such as Monte Carlo in the design decision-making process using BIM and parametric energy analysis tools.

## **2.4 Summary**

This chapter introduced a research agenda including building performance analysis, uncertainty sources and uncertainty analysis methods in performance-driven building design, risk, deterministic versus probabilistic decision-making criteria, and the

capabilities of BIM and parametric tools to support design decision-making under existing uncertainties. The promising developments of the parametric and BIM tools encourage the development of an integrated BIM-based probabilistic tool for building performance optimization. The capabilities of BIM and parametric tools may be used to create a framework for the integration of uncertainty analysis methods with performance-driven building design decision-making.

## CHAPTER 3

### METHODOLOGY

This chapter describes the general research methods and tactics applied in this research.

#### **3.1 Mixed Research Methodology**

This work has been developed using a mixed-research methodology. This research method allows tackling different aspects of a research with appropriate strategies and tools [84]. After conducting a relevant literature review the proposed framework has been designed based on the logical argumentation, prototyping, simulation, and experimental test cases.

This research was conducted to develop a probabilistic framework for performance-based building design decision making, using a mixed research strategy in an iterative process with six main steps:

1. **Research Gap Identification:** The research gap, questions, and significance are identified at this stage with conducting literature review.
2. **Research Objectives Identification:** Specifying the research questions leads to defining the specific research objectives to address the research problems and the existing gap.



3. Research Design: The research method is designed to determine how to achieve the goals and objectives of this research. This step involves prototyping and simulation as described below:

3.1 Prototype Development: This framework is developed based on the defined research objectives (determined in step 1). Multiple prototypes are designed to implement the developed framework and validate its usability. The prototypes are created using BIM tools, BIM API, Microsoft Excel, Rhino, and Grasshopper. This stage was highly connected to the next step (simulation).

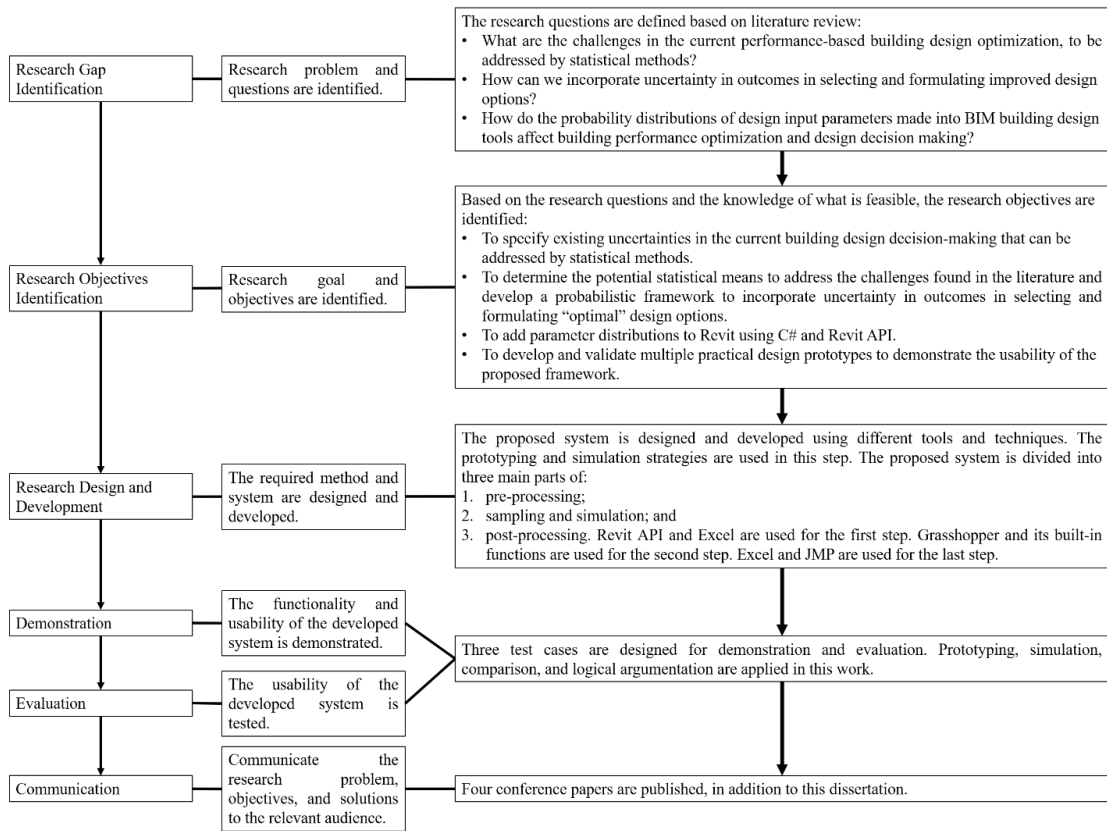
3.2 Simulation: As a main part of the developed framework, building annual thermal energy simulations were conducted using available tools including EnergyPlus and OpenStudio. In the initial phase of this research, a simplified Excel-based building energy calculator was developed to explore the potentials of using probabilistic analysis in the field of building energy analysis. The lessons learned in this phase were used to improve the framework and develop the advanced version of the framework in the second phase.

4. Demonstration: Three hypothetical building design test cases were created to test the developed framework and demonstrate the usefulness of this work. The input parameters are carefully defined, and the outputs are measured and stored for further analysis. The statistical tools and software including Microsoft Excel and JMP are used to collect, analyze, and visualize the output data.

5. Evaluation: The output data from the deterministic and probabilistic methods are compared using logical argumentation. The art of deduction and induction are used to interpret the research results and obtain the research findings.

6. Communication: The research problem, objectives, significance, and the research design are documented and communicated with other researchers in the field, performance-based building designers, and the public via this dissertation and other publications.

The research questions, objectives, and the corresponding methods and tools to find the answers are shown in Figure 3-1.



**Figure 3-1 The research methodology.**

A more detailed description of each step of this research is presented in the following sections.

### 3.1.1 Literature Review

A broad range of literature was reviewed on the existing methods of the probabilistic building performance analysis, with a focus on building energy performance. The literature review helped identifying the research gaps and questions in this field. Also, the research objectives and the potential methods and tactics to achieve them were identified based on the identified research problem, also the findings from the literature

review. The literature review was conducted as the first step of this research and continued throughout the progress of this work to update and fill the gaps when required.

In this research, the existing methods of building performance analysis including deterministic methods were reviewed. Also, the probabilistic methods and the lessons learned from other engineering fields that are using these methods were studied. The simulation tools and statistical methods were reviewed in order to develop the proposed framework. Detailed literature review was conducted in the fields of:

1. Building performance analysis,
2. Probabilistic risk assessment for building energy performance simulations, and
3. BIM and parametric tools integrated with uncertainty analysis and risk assessment.

### **3.1.2 Prototype Development**

This stage of the work consists of developing multiple prototypes using different tools to collect and transfer the data and run the simulations. The developed prototypes include:

1. A BIM addin developed using BIM API;
2. An Excel-base input variable database, and an Excel-based data collection inventory;

3. Several input sampling prototypes for the normal and Poisson distributions; and
4. A parametric energy simulation workflow in Grasshopper.

The proposed framework was developed using the combination of the developed prototypes. The developed prototypes were tested and improved iteratively throughout the research using the results from the test cases.

### **3.1.3 Statistical methods**

In this research, statistical methods refer to 1) sample generation using two probability distributions including normal and Poisson, 2) running a high number of simulations automatically and in a structured format, and 3) apply statistical techniques to visualize and analyze the outputs. These three steps are required for Monte Carlo uncertainty analysis as the proposed strategy to support building design decision-making under uncertainties. Also, the results are used for three different decision-making criteria (expected value, maximax, and maximin), to assist design decision-making considering different attitudes towards risk.

In this approach, simulation and experimental test cases are the two key features to develop and apply the proposed process.

#### *Simulation*

The combination of experiments and simulation is a common research strategy in the field of architecture [84]. There are multiple representations of the test case buildings

presented in this research. The building annual thermal loads are predicted using the simulation tools and the results obtained from the deterministic and probabilistic methods are compared.

### *Experimental Test Cases*

Three test cases are designed to specify the impact of the developed framework on building design decision making and demonstrate the usability of the proposed framework in different design scenarios:

1. The first experimental test was conducted on a hypothetical residential unit in College Station, Texas. This work was presented at the CAADRIA 2019 conference [85].

2. The second case was tested on a hypothetical classroom test case in Los Angeles, California. This test case was obtained from a research done by [86].

3. The third test was conducted on a hypothetical mid-rise office building in Chicago, Illinois.

Test cases 2 and 3 are submitted to the IBPSA 2021 conference, and CAAD Futures 2021 conference, pending the peer review.

Different building functions and climate zones were selected for the different test cases, in order to show the applicability of the proposed framework to different design scenarios.

### **3.1.1 Logical Argumentation**

According to [84] the art of logical argumentation “*tends to take a set of previously disparate factors, or previously unknown and/or unappreciated factors and interconnect them into unified frameworks that have significant and sometimes novel explanatory power.*” In this research, the comparison groups and the tactics of deduction and induction are used to define relationships between the independent and dependent variables.

*The use of comparison groups, deduction, and induction*

The deterministic method is compared with the probabilistic method in terms of the design decision making process and outcome. The results are discussed using deduction and induction.

### **3.2 Summary**

This chapter briefly described the methodology of this research.

## CHAPTER 4 <sup>1</sup>

### PROTOTYPE DEVELOPMENT

A growing demand for handling uncertainties in building energy performance simulation has challenged the conventional deterministic tools and, thus researchers in this field lean towards viable alternatives, e.g., probabilistic methods. This research addresses the challenges associated with conventional methods of performance-driven building design, i.e., ignoring the existing uncertainties and lacking a systematic framework to incorporate probability and risk assessment in building performance predictions. The main goal of this work is developing a framework to handle uncertainties and risks involved in the process of performance-driven building design decision-making.

The promising developments of BIM technologies encourages the application of probabilistic methods in architectural building design to overcome the uncertainties and predict risks in the process of design decision making. Built upon the previous work on the applications of uncertainty analysis in building energy analysis and the initial framework developed by the author and colleagues [87], this research introduces an advanced framework, BIM-based Probabilistic framework (BIMProbE), to integrate BIM-based parametric tools with building probabilistic performance analysis. This integrated framework allows generating the samples, running the simulations, and presenting the probabilistic results. Three test cases are designed to demonstrate the applications of the initial and the advanced framework. The first test case is a hypothetical single-family

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<sup>1</sup> Reprinted with permission from material published by the author and advisor in Ref. [85]



residential unit in College Station, Texas, the second test case is a hypothetical elementary classroom in Los Angeles, California, and the third test case is a multi-story office building in Chicago, Illinois.

#### **4.1 The initial workflow**

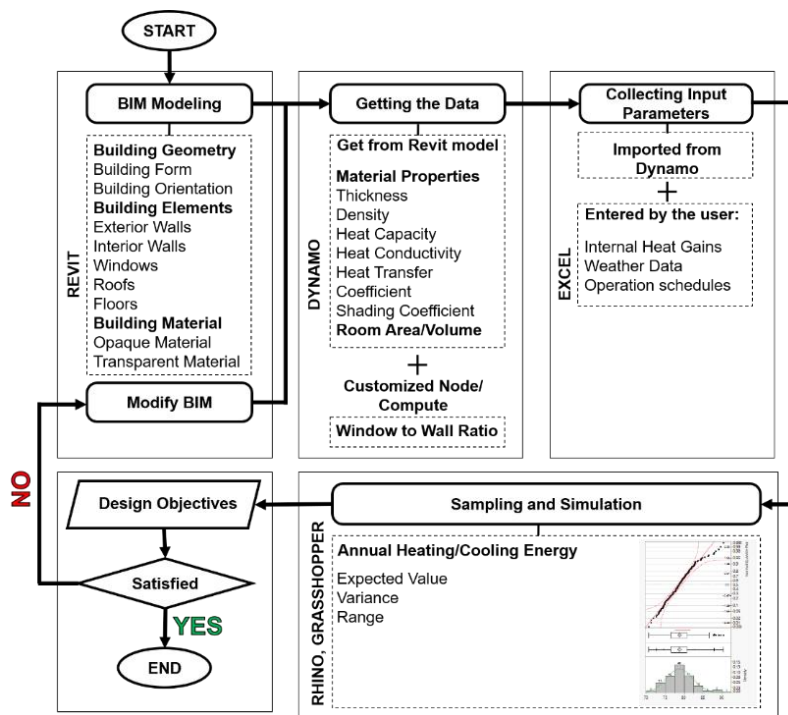
For developing the initial framework, the architectural building model was created in Revit, a BIM-based authoring tool, and Dynamo was used to retrieve design input parameters for energy simulation. This information was exported from BIM to a spreadsheet-based energy calculation tool developed for building thermal energy performance assessment. The single input values of parameters, transferred from BIM, were converted to a range of values with a probability distribution defined by the user in Excel. The random samples were generated using the Latin Hypercube Sampling (LHS) technique, and the calculations were run many times to obtain the probability distribution of the output. Using the Monte Carlo approach for uncertainty analysis, the probabilistic predictions of building performance was presented to the designer in an Excel-based GUI, developed by the author. Test case 1, presents the application of this workflow in a hypothetical building design decision making scenario.

The first step in the initial framework is modeling the building in a BIM authoring tool, i.e., Revit and setting the physical and thermal parameters of the building model. Next, the input parameters are retrieved and exported from Revit to an energy calculation tool developed by the author and colleagues. The BIM data management capabilities, and the visual programming software, Dynamo are deployed to automate the process of building information collection. The building information collected for the building

probabilistic energy analysis consists of the physical and thermal properties of building materials, also building dimensions and the Window-to-Wall Ratio (WWR). The required algorithms are developed in Dynamo to perform these tasks.

The mean values of building materials' thermal properties are collected and inserted to the developed data inventory. A user can override the input data in the Excel-based inventory as needed, also input the standard deviation values for the design inputs. A script is developed in Fortran to generate random samples of the uncertain input parameters from normal distributions. The energy calculation process is run for all the samples to obtain the probability distribution of the result. The input uncertainties propagate through the model to create the probability distribution of the output. The energy calculations are conducted using a model-based energy calculation tool, developed in Microsoft Excel [87].

Figure 4-1 elaborates the initial probabilistic framework for building energy analysis and design decision-making.



**Figure 4-1 The proposed BIM-based framework for probabilistic design.**

As shown in Figure 4-1, the first step in the proposed framework is creating a BIM model in Revit. In this phase, building geometry and the mean values for materials' thermal properties are defined by the user to identify the physical and thermal parameters of the building elements. A standard deviation value for each input parameter is specified in the later phases to perform the probabilistic energy analysis. There are three types of inputs parameter for building energy calculation, which are accessible from the Revit model:

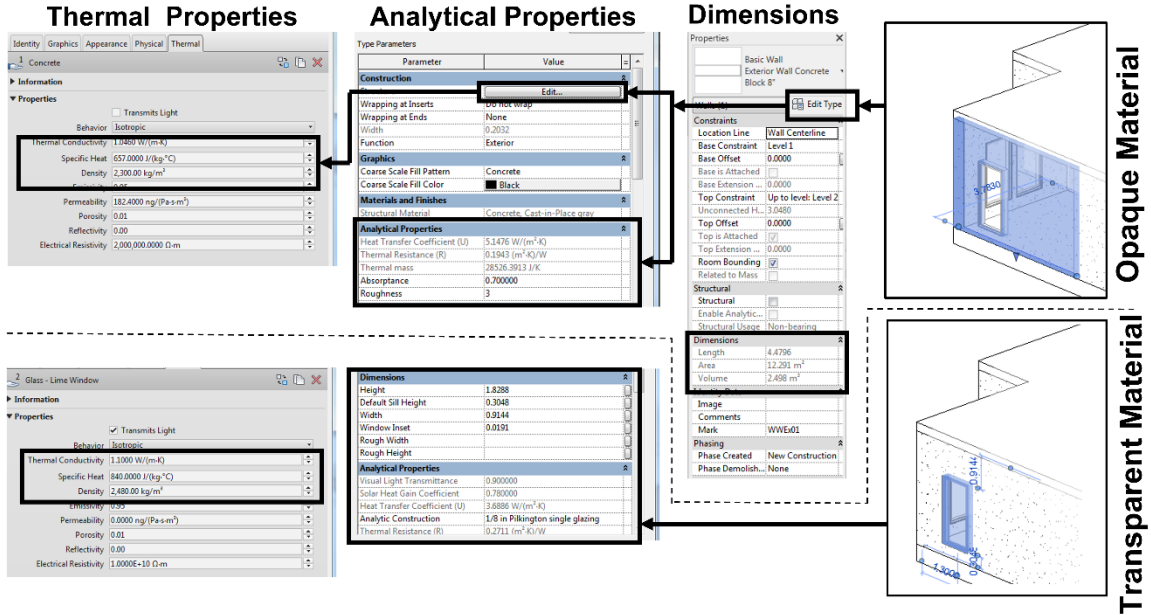
- The dimensions of building elements such as height, width, area, and volume.
- The analytical properties of opaque materials including the heat transfer coefficient (U-value), and the analytical properties of transparent materials

consisting of Solar Heat Gain Coefficient (SHGC) and heat transfer coefficient (U-value).

- The materials' thermal properties including density, specific heat capacity, and thermal conductivity.

The mean values of the thermal properties of building materials, the area and volume of the rooms, and WWR are directly or indirectly accessible in the Revit model. The internal heat gain loads, building operation schedules, and weather data, also the standard deviation values are set in the Excel-based energy calculator spreadsheet, manually. The mean and standard deviation values of each input parameter are used as seed values to generate samples of inputs with normal probability distribution functions. Random sets of values, corresponding to the input parameters, are selected from normal distributions to execute energy calculations, repeatedly. The calculation outputs are collected and presented with histograms and frequency curves, to conduct uncertainty analysis and risk assessment for design decision making. The designers should continue developing new design options and modifying the BIM model until design objectives are satisfied.

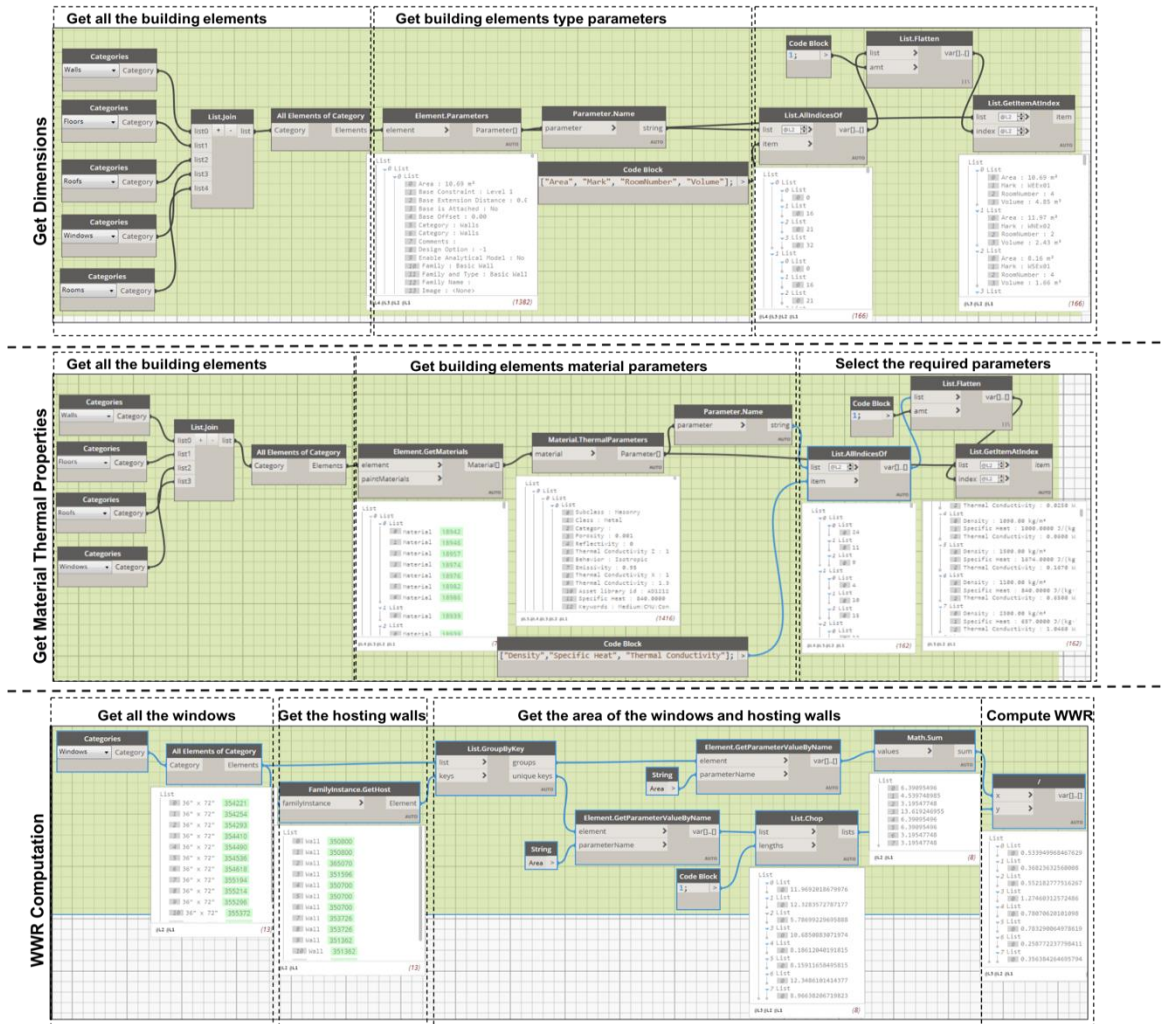
The user can define the dimensions of the elements and materials' properties with creating object families and assigning the building materials in Revit. Figure 4-2 indicates the physical and thermal properties of a sample opaque material, also a sample transparent material in Revit.



**Figure 4-2** The physical and thermal parameters of building elements accessible in Revit.

A mapping between Revit and Excel is performed through Dynamo, the BIM visual programming interface, to retrieve the input parameters from the BIM model. The building material properties, the dimensions of building elements, and the WWRs are transferred from the Revit model to the Excel-based energy calculation tool developed by [87]. Each input parameter is either directly or indirectly available in the Revit model. The directly available parameters including building materials' thermal properties are accessible using the built-in nodes in Dynamo, i.e., `Element.GetParameterValueByName` and `Element.GetMaterial`. The indirectly available parameters are those that need to be computed using other available parameters. For instance, WWR is not immediately accessible from the Revit model, but can be calculated using 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 4-3 illustrates the developed scripts in Dynamo to collect WWRs and other indirectly available parameters from the Revit model.

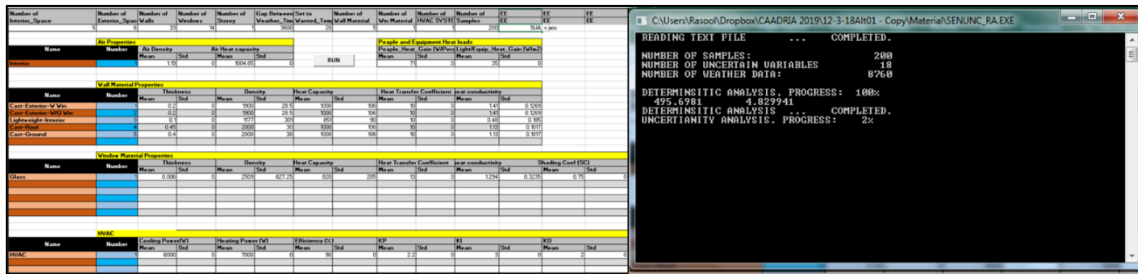


**Figure 4-3** Extracting directly accessible and indirectly accessible parameters from the Revit model in Dynamo.

The building annual thermal load is calculated using the Excel-based building energy calculator. Two hundred samples of each design option are generated with a

random normal sampling technique, and the calculations are run to estimate the building energy performance.

The model-based energy calculation tool is developed in Fortran, having a Graphical User Interface (GUI) in Microsoft Excel [87]. The user chooses the mechanical parameters, i.e., HVAC efficiency and heating/cooling power from the predefined drop-down menus in the Excel-based calculator. Besides, the weather data in .csv format is required to run the simulations. Using the developed GUI, user can define a standard deviation value for each input variable. The expert judgment or the findings from previous research could be good sources for standard deviation values selection. Figure 4-4 depicts an overview of the developed GUI in Excel.



**Figure 4-4 An overview of the developed building energy calculation GUI.**

The user defines the number of samples in the GUI to start sampling and energy calculation. Building annual thermal load is calculated using the spreadsheet-based energy calculator.

The reason to use an Excel-based calculation tool, instead of other energy simulation tools such as EnergyPlus is the simplicity and the capabilities of this tool to generate samples, run the calculations and present the results in a single user interface that allows exploring the application of probabilistic methods for building energy analysis. The

model-based calculation tool is simplified to run the calculations with a limited number of input parameters. This feature makes the process of probabilistic analysis faster and more efficient, without requiring too many input features. This energy calculator could be replaced by other energy simulation tools, but it would need adjustments in the type of input variables to run the energy simulations. The replacement of this part is discussed in the development of the advanced framework.

#### **4.2 The advanced workflow**

The previous workflow (initial framework) had some challenges including the manual process of entering the standard deviation values in the Excel GUI, also being disconnected to the commonly used energy analysis software such as EnergyPlus and OpenStudio. The result obtained from the previous workflow was oversimplified due to the simplifications of the developed energy calculator in Excel. The advanced workflow tackles the challenges involved in the previous workflow with linking the BIM model to a database (developed in Excel, based on the literature review), adding the probability distributions of building material inputs in Revit, and coupling BIM modeling with parametric energy analysis in an automatic process.

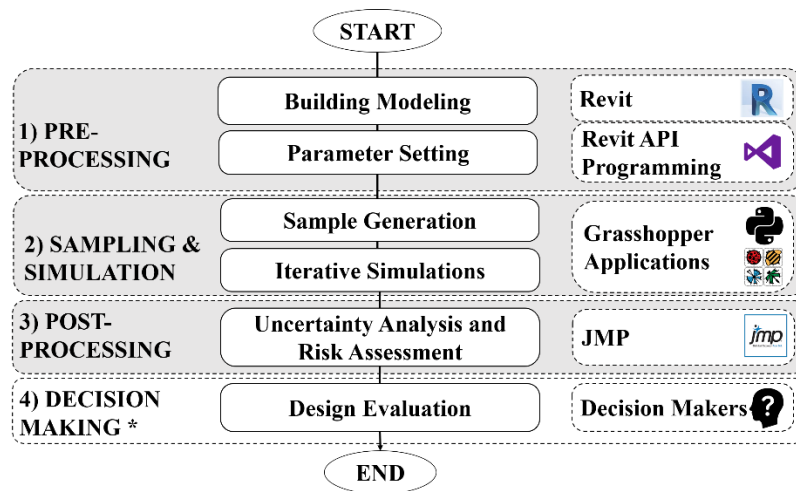
This study presents a new framework to implement probabilistic methods in the field of performance-driven building design decision-making, using Building Information Modeling (BIM) and parametric tools. This framework considers uncertainties in building energy simulations including material properties and proposes integrating BIM to provide the input data for uncertainty analysis. The BIM parametric capabilities allow the



automation of input collection for the building analysis models. Three main features of the developed framework (BIMProbE) are:

1. BIMProbE includes building physical and thermal parameters concerning building energy performance and considers the variations of the input as the primary source of uncertainties.
2. BIMProbE facilitates retrieving the probability distribution of building materials from Revit and automation of updating input data according to the Revit architectural model.
3. The user can override the input data in Excel as needed.

This framework allows the evaluation of design options not only based on their predicted performance but also the probability of their occurrence using Monte Carlo approach. Test cases 2 and 3 demonstrate the applications the advanced framework. The workflow of this framework is illustrated in Figure 4-5.



**Figure 4-5 The proposed probabilistic framework for performance-based design decision-making.**

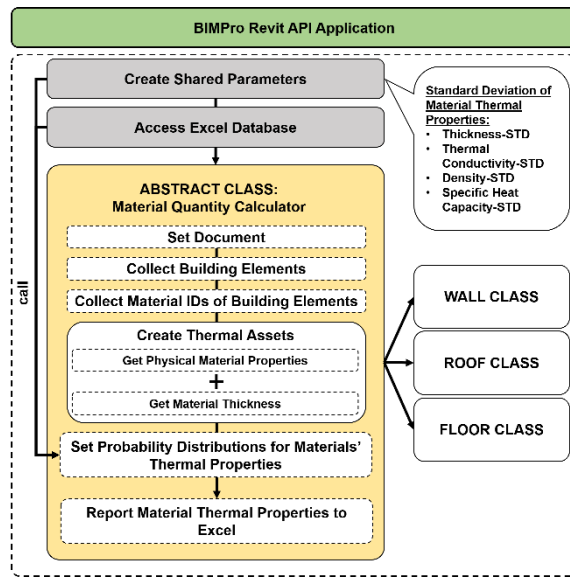
The proposed framework consists of three key steps of pre-processing, sampling and simulation, and post-processing to support design decision-making.

#### **4.2.1 Pre-Processing**

The pre-processing phase consists of three parts of building modeling in a BIM authoring tool, i.e., Revit, assigning building materials for building elements, and using the BIM API to create a probability distribution for the thermal properties of building materials. One of the contributions of this research is developing a BIM plugin to facilitate this process.

##### *BIM API*

The building geometry is modeled in Revit and the developed Revit addin is used to set the probability distributions for thermal properties of building materials based on the real-world material properties learned from literature studies and retrieved from an external database (Microsoft Excel). The mapping between Revit and Excel to retrieve the input parameters from the BIM model is performed through BIM API. The object-oriented programming is used to create this connection between Revit and Excel to read the data, also write it back to a new spreadsheet to be used in the later steps of sampling and energy simulations. Figure 4-6 illustrates the workflow of the developed plugin for Revit.



**Figure 4-6 BIMProbE development for getting and setting probabilistic distributions for thermal properties of building materials.**

BIM capabilities allow the user to add family or shared parameters to a Revit component using BIM API. The shared parameter is chosen for the purpose of this research because the family parameters cannot be created programmatically [88]. Moreover, the family parameters cannot be added to multiple projects and families, and do not appear in the schedules. An external application named as BIMProbE, is developed for Revit to facilitate the probabilistic analysis for architectural design decision making. The workflow of this process is described below:

*Creating shared parameters*

In this study, there are four shared parameters created for the building materials category: 1. Thickness standard deviation; 2. Thermal conductivity standard deviation; 3. Density standard deviation; 4. Specific heat capacity standard deviation.

### *Connecting Revit to a database to set probability distribution of inputs*

BIMProbE addin will automatically create the shared parameters and bind them to each building material in the project, and search for the material names in the Excel database to assign the correct values to the parameters. This process begins with an attempt to open the external Excel database. Once the user starts this addin, a window will pop up asking the user to select an external Excel file. If the user selects an Excel file, the program will automatically start reading it cell by cell. The program will check the sanity of the data first and if there is no error found, it will continue with the rest of this process.

### *Collecting building elements in Revit*

Building elements consist of exterior walls, interior walls, roofs, floors, and windows. The material thermal properties including thickness, density, specific heat capacity, and thermal conductivity are required in building energy exchange equations conducted in energy analysis software such as EnergyPlus and OpenStudio. This program will find and collect opaque components including walls, roofs, and floors.

### *Accessing and creating building materials thermal asset*

The material IDs associated with each material is identified to collect the thermal properties. The thermal properties of building materials including thickness, thermal conductivity, density, and specific heat capacity can be collected from the BIM model. The thickness can be accessed as the width of each layer of the building components. For instance, a Structurally Insulated Panel (SIP) wall type consists of six layers of Plasterboard, Wood, Timber Insulated Panel – OSB, Timber Insulated Panel – Insulation, Timber Insulated Panel – OSB, and Sand/Cement Screed. The width of each layer of an

SIP wall can be identified as the thickness of that specific material. Other thermal properties of materials including thermal conductivity, density, and specific heat capacity can be directly accessed in the thermal assets of each building material. If the thermal properties of a material are missing, the program will create a thermal asset for that material and will set the thermal properties according to the corresponding values in the Excel database. To get the thermal properties of building materials and assemblies in Revit, there are two options:

1. Getting the thermal properties of each layer of material (including thickness, thermal conductivity, density, and specific heat capacity) and using this information to construct a building assembly, e.g., building walls in Grasshopper and run energy simulations with this information (this method is used in test case 2).
2. Getting the R-value of each building assembly, e.g., building wall, and run energy simulations using the R-value and the thickness of building elements (this method is used in test case 3).

The mean and standard deviation values of the first four thermal properties of building materials, are mostly available in the literature, but the probability distribution of the R-value of the building materials are not discussed as much in the previous works based on literature review. The R-value of a building material could be calculated using the following formula:

$$R\_value (m^2K/W) = \frac{\text{Material Thickness (m)}}{\text{Thermal conductivity (W/mK)}}$$

(Note: Thickness and thermal conductivity (coefficient) are assumed to be independent parameters with normal distributions).

With the probability distributions of material thickness and thermal conductivity, the probability distribution of R-value could be obtained through two solutions:

1. With two independent random variables of X and Y, using a ratio distribution leads to:

$$E\left(\frac{X}{Y}\right) = E(X)E\left(\frac{1}{Y}\right)$$

$$V\left(\frac{X}{Y}\right) = E\left(\frac{X^2}{Y^2}\right) - \left[E\left(\frac{X}{Y}\right)\right]^2$$

where  $E\left(\frac{X}{Y}\right)$  is the mean and  $V\left(\frac{X}{Y}\right)$  is the variance of the ratio distribution. These results follow from the fact that when random variables X and Y are independent, then  $E(XY)=E(X)E(Y)$  [89].

2. The mean or variance of (XY) for a few specific cases could be calculated using simulation. With generating millions of pairs (X,Y), and computing  $\left(\frac{X}{Y}\right)$  for each pair, the sample mean and variance of the millions of values of  $\left(\frac{X}{Y}\right)$  could be calculated.

In test case 3, the second method is used to identify the probability distribution of R-value and generate the samples.

*Writing the probability distributions of input parameters to a data inventory in Excel*

The probability distributions (including the mean and standard deviation) for each material type are set according to the corresponding values in the Excel database. BIMProbE allows writing the mean and standard deviation values of the thermal properties to a new Excel spreadsheet to be used for later steps of sampling and simulation in Grasshopper.

#### **4.2.2 Sampling and Simulation**

Sampling-based probabilistic uncertainty analysis using Monte Carlo simulations is the most commonly-used technique in building performance simulation [3]. This approach does not treat the design problem as a deterministic model and run the simulations many times. This research deploys the capabilities of the BIM and parametric design tools including Revit and Grasshopper to apply Monte Carlo uncertainty analysis in the field of building energy analysis for design decision making.

In the sampling and simulation phase, a number of values for input parameters are generated from a normal or Poisson probability distribution. The simulation process is run for all the samples and the input uncertainties propagate through the model to create the probability distribution of the output. In this research, the simulations are conducted using commercial energy analysis tools, including EnergyPlus and OpenStudio. These simulation engines are available in Grasshopper, the visual programming software for Rhinoceros.

The Monte Carlo process is based on random processes with specific probability distribution types. A random process includes a sequence of random variables  $X_1, X_2, X_3$ , etc. that are usually indexed by time. Each variable can take on a different value from some probability distribution. This process can work with either discrete or continuous input variables. Two probability distribution types including the normal distribution and the Poisson distribution are used to generate the samples for the input parameters associated with uncertainties. This research selects normal or Poisson probability distribution type for each input variables based on the findings of the previous research.

For variables with normal probability distribution, the mean and standard deviation values for input variables are obtained from the existing literature [22], [25], [90], [91] . Among different resources in this field, the work of Lomas and Eppel [91], is one of the most cited references. However, this reference identifies the probability distribution of the input parameters with three values of minimum, mode, and maximum. In this research, the mean and standard deviation values are required to insert into the system. The “range” rule of thumb is introduced in some of the previous research [92] to calculate the standard deviation with having the minimum and maximum values:

$$\text{Standard deviation} \approx \frac{\text{sample range}}{4}$$

However, it is proven that the “range” rule of thumb only works for a normal distribution with a small sample size (around 30) [93]. Through the use of Monte Carlo simulations, there is a suggested improvement to the range rule of thumb for the normal probability distribution [94] :



$$\text{Standard deviation} \approx \frac{\text{sample range}}{3\sqrt{\ln n - 1.5}}$$

However, the “n” parameter (the number of samples) is unknown in the references that we have. Therefore, the data learned from a more recent reference is used in this research that presents the probability distributions with the mean and standard deviation [25].

According to Zhou et al. [95], the Poisson distribution could be the most suitable representative for the building design parameters related to occupants’ behavior, including building occupancy, lighting, and equipment internal heat gain loads.

Remember, for a discrete random variable  $x$  with a Poisson distribution, the probability mass function (PMF) of  $x$  is defined by:

$$P(k \text{ events in interval}) = e^{-\lambda} \frac{(\lambda)^k}{k!}$$

where, parameter  $\lambda$  (the average event rate) is greater than 0,  $k$  (the number of times an event happens in an interval) = 0, 1, 2, ..., and  $e$  is Euler's number ( $e = 2.71828\dots$ ).

To create 500 samples with a Poisson distribution for some of the design inputs in test case 3, the Numpy package in CPython is used, and the average (mean) values for the design inputs are collected from the literature, and plugged into a Python script as parameter  $\lambda$ .

Latin Hypercube Sampling (LHS) method is used in this research for the input variables with normal distribution. For those variables with Poisson distribution, random sampling is applied. The LHS procedure takes in the input variables and creates random

pairs of samples efficiently. Let us start with an example with only two input variables,  $U$  and  $V$ . The range of  $U$  is divided up into  $M$  intervals having equal probability. The same is done for  $V$ . Now,  $M$  values of  $U$  are selected, one from each interval (This can be done in such a way that the overall sample of  $M$  variables is normally distributed.). Also,  $M$  values of  $V$  are selected, one from each of its  $M$  intervals. Then random pairs the values of  $U$  and  $V$  are selected. Let us say the values of  $U$  are  $U_1, \dots, U_M$  and the values  $V$  are  $V_1, \dots, V_M$ . The process is started with  $U_1$  and randomly selecting one of  $V_1, \dots, V_M$  to pair with it. Then, it goes on with  $U_2$  and randomly selects one of the remaining  $M-1$  values of  $V$  to pair with  $U_2$ . This process is continued in this way until all values are paired up. This process needs fewer samples to converge [3]. Let the rows correspond to  $U$  and the columns to  $V$ . The first pair will be in row 1 and, say, column  $j$ ,  $j$  being the randomly selected index for  $V$ . Now the next pair will be in row 2 (a different row), and the column will not be  $j$  because we pick only from the remaining columns. The same thing will be true for every pair. It will be in a different row and column than the previous values. For instance, in test case 2, there are 11 input variables. Each input variable has 500 samples, randomly positioned in a list. Each value in each list has an index (starting from 0 to 499). Since each list is random itself, then paring the values from each list, starting from index 0 and going up to index 499, guarantees the randomness of the combinations.

Tian et al. (2018) [1] recommend the general sample size for a LHS method to be ten times the number of variables in computer experiments. In previous works, the number of samples for energy simulations with the LHS method were 500 samples in [2], 200

samples in [3], 100 samples in [6], and 100 samples in [5]. Referring to the recommended sample size by the existing literature and previous studies related to our work, 200 samples for test case 1 and 500 samples for test cases 2 and 3 are reasonable numbers for this analysis.

#### *Building energy performance simulation*

The probabilistic simulations are conducted in Grasshopper using the statistical tools programed in CPython and simulation applications available in Ladybug tools (with the EnergyPlus and OpenStudio simulation engines). The CPython component in Grasshopper is used to import the statistical tools such as Numpy and Scipy into Grasshopper (Abdel Rahman, 2018) to generate input samples.

The building geometry is created using the parametric capabilities of Grasshopper. This part could also be done by exporting the model from Revit to Rhino or using a new development known as Rhino.inside.Revit. The building mass is split to floors and thermal zones using the existing components in Grasshopper. The Window-to-Wall Ratio (WWR) for each façade is parametrically set in Grasshopper. The mean and standard deviation values of the thermal properties of building materials are set according to the Excel data inventory (created using BIMProbE).

The internal heat gain sources and the HVAC settings are set in Grasshopper based on the findings of the previous research. The occupancy, lighting, and equipment operation schedules are set, and the thermal zones are exported to IDF files and run through EnergyPlus (test case 2) or OpenStudio (test case 3) in Grasshopper. The energy simulations are programmed to start automatically and run using the generated input

samples. To automate the random value selection for each input parameter and run EnergyPlus for N (number of samples) times, a number slider, that is remotely controlled (“Grasshopper3D”, 2017), is connected to the list of input variables and selects an index of each list (starting from 0 and ending at N-1) automatically and feeds the associated input value to the simulation. The simulation outputs is the building annual thermal load calculated in kWh/m<sup>2</sup>. The outputs are collected and stored in Excel for post-processing.

### **4.2.3 Post-Processing**

The post-processing phase consists of the graphical presentation of the results and data analysis. This phase is conducted using software JMP. The data are collected in Grasshopper and exported to Excel for post-processing. The JMP [8] addin for Excel provides interactive graphics and tables that enable the user to identify relationships visually and examine patterns. The data post-processing provides a visual format of the data to make them easily understood by the user. The outputs of the post-processing are used to interpret the probabilistic simulation outputs, conduct risk assessment, and make informed design decisions.

#### *Data collection and visualization*

The simulation outputs are recorded in Grasshopper written to Excel using TT Toolbox plugin for Grasshopper [96].The histogram demonstrations, normality plots and box plots are used for data visualization and risk assessment.

### **4.3 Summary**

This chapter described the proposed probabilistic BIM-based framework for performance-driven building design decision-making. This research proposes a new

framework to implement probabilistic methods in the field of building thermal energy analysis. Two workflows are proposed in this research: 1. the initial workflow; and 2. the advanced workflow.

The initial workflow deploys Revit, Dynamo, and Excel to apply Monte Carlo uncertainty analysis in building thermal energy consumption calculations. The initial workflow was a starting point, trying to use a fast simulation method and highlight the statistical part of the work. However, the initial workflow is not recommended, because of the existing challenges.

The advanced workflow integrates a building design process with Monte Carlo uncertainty analysis using BIM API and parametric tools in Grasshopper (See Appendix 1). The scripts related to each step can be found at this address: <https://github.com/Aban6?tab=projects>.

This study considers several sources of uncertainties in building energy analysis with two different probability distributions: Normal and Poisson. The simulation outputs provide predictions about the possible range of building thermal energy consumption. Three test cases are designed for demonstration in Chapter 4, and the probabilistic predictions are discussed and compared with deterministic results obtained from a conventional method in Chapter 5.

## CHAPTER 5 <sup>2</sup>

### TEST CASES

This chapter describes three test cases designed to validate the usability of the proposed framework for performance-driven building design under uncertainties.

#### 5.1 Three test cases

The test cases were studied to demonstrate the workflow and applications of the developed framework. Table 5-1 lists the names, building types, locations, and climate zones (based on the ASHRAE 90.1) of the test cases.

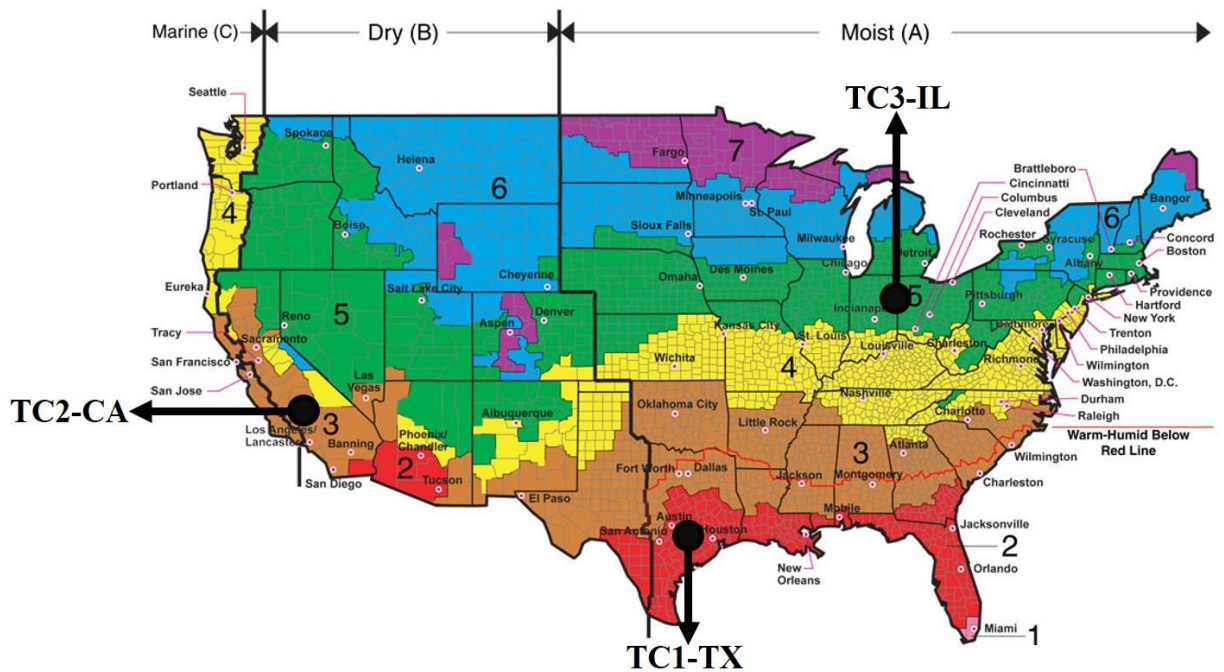
**Table 5-1 The description of the test cases.**

<b>Test Case</b>	<b>TC1-TX</b>	<b>TC2-CA</b>	<b>TC3-IL</b>
<b>Building Type</b>	Single Family Residential Unit	Elementary Classroom	Multi-story Office Building
<b>Location</b>	College Station, TX	Los Angeles, CA	Chicago, IL
<b>Climate Zone</b>	2A	3B	5A

The test cases are selected in three different states in the United States, including Texas (climate zone 2A), California (3B), and Illinois (5A). Figure 5-1 depicts the locations of the test cases on the USA map, separating different climate zones.

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<sup>2</sup> Reprinted with permission from material published by the author and advisor in Ref. [85]



**Figure 5-1 The climate zone map of the test cases [104].**

Test case 1 (TC1-TX) presents a hypothetical building design problem focusing on the building materials' thermodynamic properties. This test case is extracted from the author's previous work published in CAADRIA 2019 conference [85] to introduce the concept of drawing the building information for probabilistic building energy analysis using the Building Information Modeling (BIM) tools. The building is located in College Station, Texas and three different sets of building materials are compared for the building envelope to achieve a better energy performance. The building is modeled in Revit, and Dynamo (a visual programming program in Revit) is used to collect the physical and thermal information about the building materials. This test case is designed to demonstrate the capabilities of BIM tools including Revit to collect building design information. An energy calculator in Microsoft Excel is used to calculate the building annual thermal

energy consumption and compare the deterministic results with the probabilistic results. This tool was selected due to simplicity and its capabilities in exploring probabilistic results without requiring too many input variables. The main goal of this test case is to explore and demonstrate the capabilities of the BIM tools for probabilistic building energy analysis. The emphasis of this test case is on the Dynamo workflow. The validation of the calculator tool requires further studies and is out of the scope of this research. This energy calculator is replaced with other validated and commonly used commercial simulation tools such as EnergyPlus and OpenStudio, in the next two test cases.

Test case 2 (TC2-CA) studies a hypothetical building design scenario with three different design options. This test case is located in Los Angeles, California. The main design objective is to minimize the building annual thermal load (the sum of cooling and heating loads), and the design variables include building layout, roof slope, Window to Wall Ratio (WWR), building envelope materials, and internal heat gain sources. Three different design options are compared in terms of building energy performance. TC2-CA presents an example of building energy performance assessment based on some input variables with Normal distributions to obtain probabilistic results using the proposed framework. The object-oriented programming using BIM API is deployed to create an addin for Revit and collect the building components and set the thermodynamic properties of building materials based on an existing dataset. The building energy consumption is simulated using the Ladybug tools and EnergyPlus simulation component available in Grasshopper, the visual programming environment of Rhino. The probabilistic results are



compared against the deterministic results and the effects of each method on the design decision-making is discussed.

Test case 3 (TC3-IL) presents another hypothetical building energy analysis problem to further demonstrate the applications of the developed framework based on input variables with normal and Poisson distributions. In this test case a multi-story office building in Chicago, Illinois is simulated using deterministic and probabilistic methods. In the first phase of this experiment, three design options are developed and compared to find the best building energy performance. The best option is then compared with a new design option in the second phase. The main goal of this study is to find the best building energy performance among the available options. The design variables are the thermodynamic properties of building envelope materials, HVAC system settings, and the internal heat gain sources. The building is modeled in Revit and the thermal properties of building materials are collected using the developed plugin in Revit. The building energy consumption is simulated using the Ladybug tools and OpenStudio simulation component available in Grasshopper, the visual programming environment of Rhino. The results are compared using deterministic method and the proposed probabilistic method. The results are thoroughly discussed in the next chapter.

## **5.2 Design Experiment Assumptions**

For the three test cases, the building annual thermal load (the sum of heating and cooling loads) in kWh/m<sup>2</sup> is defined as the target. The test cases study the effects of some of the existing uncertainties including the thermal properties of building materials, HVAC

characteristics (considered only in TC3-IL), internal heat gain loads, ventilation rate, infiltration rate, and occupant behavior on the of building annual thermal load.

During the analysis, we use  $X$  to denote the space of input values and  $y$  to denote the output value, hereby written as,

$$y = f(X)$$

The building annual thermal load is evaluated using two different methods: the conventional (deterministic) and the (proposed) probabilistic methods, that are compared to illustrate the benefits of the proposed probabilistic method in the process of building design decision making. The probabilistic analyses in test cases 2 and 3 uses a parametric model to derive multi-input and multi-output models for the test case buildings.

The set of  $X = \{x_1, x_2, x_3, \dots, x_n\}$  shows the independent variables in this study, while  $y$  denotes the dependent variable. In the conventional method, the uncertain factors and measurement errors are ignored, and the  $y$  is a single output calculated based on a fixed set of  $X$  variables. However, design decision making with a probabilistic approach is based on the relationship between the input vector  $X$  and the output  $y$  which is specified by a joint probability distribution  $P_{X,y}$ . Indirect knowledge about  $P_{X,y}$  can be obtained through an independent and identically distributed samples In this research, the Monte Carlo method is applied to study the uncertainties in the input variables and conduct an uncertainty propagation through the output  $y$ .

In the probabilistic approach, the set of  $X = \{x_1, x_2, x_3, \dots, x_n\}$  consists of two subsets of  $X_{det}$  and  $X_{uncer}$ . The subset  $X_{det}$  refers to those design parameters that are considered to be fixed, while  $X_{uncer}$  denotes those parameters that are associated with some uncertainties and vary according to their associated probability distributions. The following assumptions are made prior to the conduction of each experiment (Bengea et al. 2011):

(a) The surface temperatures of both walls and windows are assumed to be uniform all over the surface, hence, are represented using single-value variables.

(b) The heat transfer coefficient is temperature independent and uniform over a wall or window surface.

(c) The thermal properties of walls and windows are temperature independent.

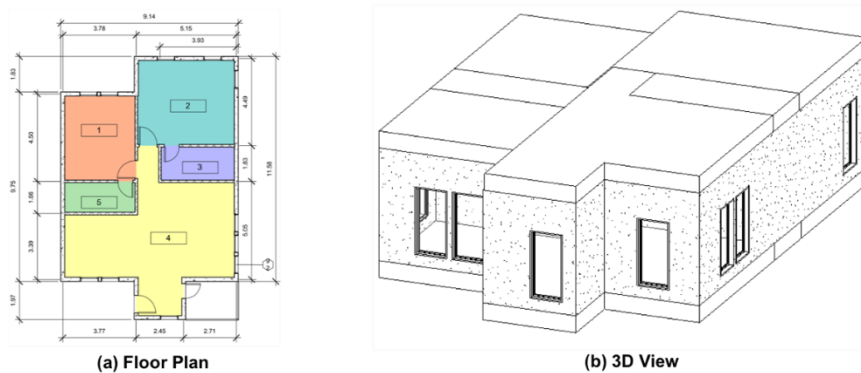
(d) The weather file for each location is downloaded from the EnergyPlus website for the energy simulations [97].

### **5.3 Test Case 1 (TC1-TX)**

In this test case, a hypothetical residential unit is designed to present the initial proposed workflow of building information collection using the BIM tools including Revit. This information is required by the proposed framework for probabilistic building energy analysis and design decision-making. The building model is located in College Station, Texas, that is considered as climate zone 2A based on the ASHRAE 90.1 (ASHRAE 90.1, 2013) standard. This test case studies the effects of the existing

uncertainties in the thermal properties of building materials on the building annual thermal load. Three design options with different sets of building materials are compared to find the lowest building annual thermal load.

This test case reports a comparison of three envelope design options for a hypothetical building model to display the capabilities of the proposed framework in supporting probability-based design decision-making. Figure 5-2 (a) and (b) show the floorplan and 3-Dimensional views of the model base case.



**Figure 5-2 Test case 1 model in Revit.**

The building elements, i.e., exterior walls, interior walls, roof, floor, and fenestration are discussed in this analysis. Table 5-2 indicates the value assumptions for the thermal properties of the building materials, including density, specific heat capacity, and thermal conductivity. These assumptions are obtained from the literature [22]. The uncertainty analysis is conducted to evaluate three design options and select the best option in terms of building energy performance.

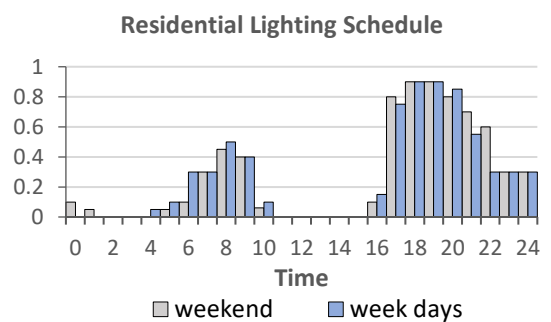
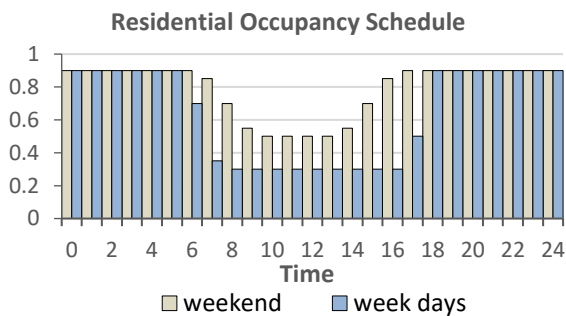
**Table 5-2 Building material thermal properties for test case 1 [22].**

	Design Options	Density $\rho$ (kg/m <sup>3</sup> )		Heat Capacity $c_p$ (J/kgK)		Thermal Conductivity $\lambda$ (W/mK)	
		$\mu$	$\sigma$	$\mu$	$\sigma$	$\mu$	$\sigma$
<b>Exterior wall construction</b>	Design Option 1.1 (Concrete)	1900	28.5	1000	106	1.41	0.1269
	Design Option 1.2 (Clay Brick)	1720	172	837	83	0.789	0.07
	Design Option 1.3 (Plywood)	622	26	1718	128	0.16	0.028
<b>Interior walls</b>	Design Option 1.1 (Concrete)	1177	301	851	90	0.48	0.185
	Design Option 1.2 (Plasterboard)	704	70	1359	130	0.191	0.01
	Design Option 1.3 (lightweight blockwork)	695	147	981	399	0.258	0.04
<b>Roof construction</b>	Design Option 1.1 (Concrete)	2000	30	1000	106	1.13	0.1017
	Design Option 1.2 (Metal)	6278	627	544	54	224	22
	Design Option 1.3 (Asbestos boards)	1488	501	958	109	0.43	0.153
<b>Floor construction</b>	Design Option 1.1 (Concrete)	2000	30	1000	106	1.13	0.1017
	Design Option 1.2 (Timber)	648	64	1845	184	0.201	0.02
	Design Option 1.3 (Timber + carpet)	831	85	3585	830	0.801	0.028
<b>Fenestration</b>	Design Option 1.1 (Clear Glass)	2509	105	820	50	1.294	0.69
	Design Option 1.2 (Clear Glass)	2509	105	820	50	1.294	0.69
	Design Option 1.3 (Clear Glass)	2509	105	820	50	1.294	0.69

The other parameters involved in this energy calculation are defined as follows:

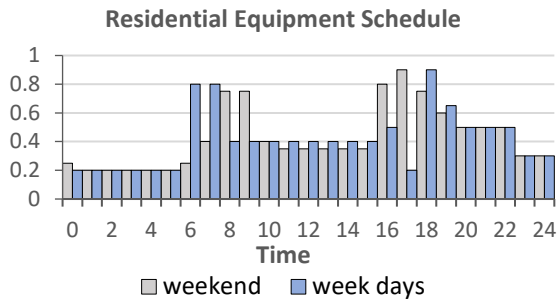
- A one-person occupant load is set for rooms 1, 2, 3, 5 and three-person occupant load for room 4 (room numbers are shown in Figure 5-2).
- The main internal heat gain coefficients are assumed as follows:
  1. occupant load=15W per person,
  2. lighting loads=15 W/m<sup>2</sup>, and
  3. equipment loads=35 W/m<sup>2</sup>.
- 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.

The operation schedules of the building are shown in Figure 5-3 (a-c).



**a) Residential occupancy schedule**

**b) Residential lighting schedule**



**c) Residential equipment schedule**

**Figure 5-3 The residential operation schedules.**

The weekday operation schedules follow similar patterns to the weekend schedules, only the magnitudes are different because the occupants are more likely to be present at home in the weekends than the weekdays. For example, Figure 5-3a) Residential occupancy schedule shows that the occupancy presence starts to decline at about 6am, stagnates at noon, and ascends gradually by 5pm where it gets fixed again (weekday/weekend).

The Excel-based energy calculator is used to generate 200 samples of the inputs and run the calculations. The post-processing phase in this framework consists of graphical presentations of uncertainty analysis. The results are thoroughly discussed in the next chapter.

## 5.4 Test Case 2 (TC2-CA)

In this test case, a modular and mobile classroom design introduced by [86] is used to demonstrate the applications of the proposed advanced framework for building energy analysis and optimization (Figure 5-4). This experiment highlights the distinctions between the proposed probabilistic approach with the conventional deterministic approach.



**Figure 5-4 Sprout Space [86].**

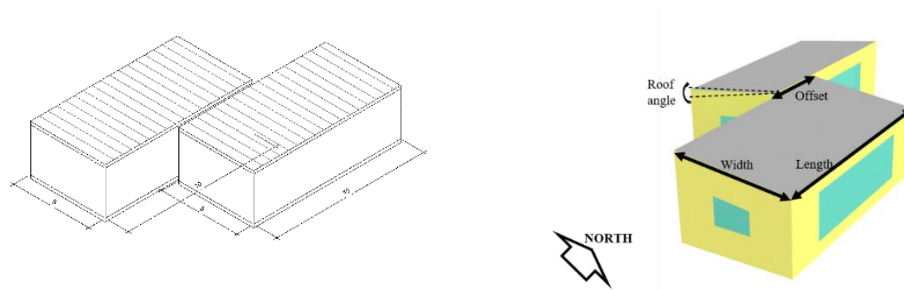
A hypothetical design optimization problem is defined of which the main objective function is to minimize the building annual thermal load. Three manually created design options of the modular building are selected to study as the design space. The physical site of this test case is in Los Angeles, California, which is considered as climate zone 3B based on the ASHRAE 90.1 (ASHRAE 90.1, 2013).

### 5.4.1 Test Case 2 (TC2-CA) Model

This test case consists of two attached rectangular plans (10m by 5m). The architectural design input parameters are the configuration of the two rectangular plans,

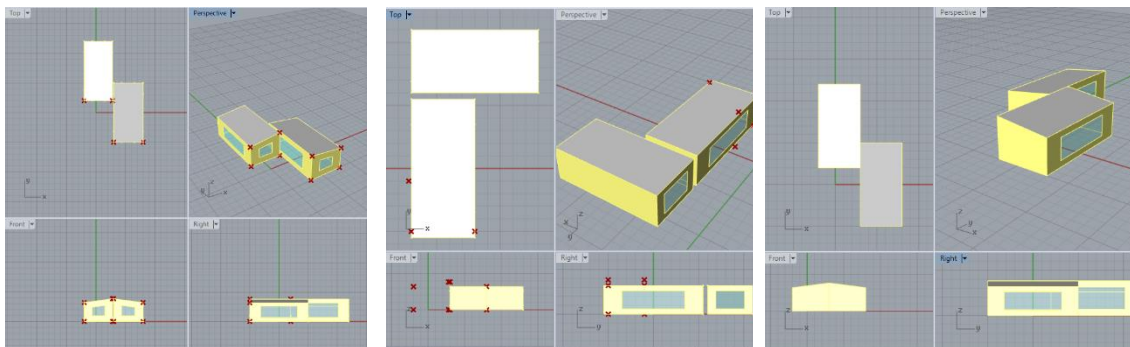


building orientation, Window-to-Wall Ratio (WWR), and the roof angle. Figure 5-5 depicts a sample of the modular design and some of the design input definitions.



**Figure 5-5 The geometric representation of test case 2 (Revit model on the left and Rhino model on the right).**

The physical parameters are defined as the thermal properties of building materials, and the design parameters are listed as the internal heat gain loads, ventilation rate, and infiltration rate, also occupancy-related parameters including occupancy, lighting, equipment, and infiltration schedules. Figure 5-6 shows the geometrical representation of the three design options studied in this section.



**Design Option 2.1**

**Design Option 2.2**

**Design Option 2.3**

**Figure 5-6 Three design options for test case 2.**

The three design options in this study are different from each other in terms of the offset amount of the rectangular plans, building orientation, WWR, roof angle and some physical parameters including the types of building materials. The design assumptions for the three selected design options are listed in Table 5-3.

**Table 5-3 Test case 2 design variable assumptions.**

<b>Variable [Unit]</b>	<b>Design Option 2.1</b>	<b>Design Option 2.2</b>	<b>Design Option 2.3</b>
<b>Orientation (North axis)</b>	0°	0° (rectangular plan1), 90° (rectangular plan2)	0°
<b>Roof slope [%]</b>	4	0	4
<b>Offset between the two plans[m]</b>	3	perpendicular	3
<b>WWR North [%]</b>	20	0	0
<b>WWR South [%]</b>	20	0	0
<b>WWR East [%]</b>	40	40	40
<b>WWR West [%]</b>	40	40	40
<b>Glazing U-value [W/m<sup>2</sup>K]</b>	2.84	0.6	0.6
<b>Glazing SHGC</b>	0.25	0.25	0.25
<b>Exterior Wall Construction</b>	Concrete Block	Structurally Insulated Panel (SIP)	Structurally Insulated Panel (SIP)
<b>Floor Construction</b>	Concrete (thickness: 0.4 m)	Concrete (thickness: 0.2 m)	Concrete (thickness: 0.2 m)
<b>Roof Construction</b>	Concrete (thickness: 0.2 m)	Concrete (thickness: 0.2 m)	Concrete (thickness: 0.2 m)

Design Options 2.1 and 2.3 are constructed of two parallel rectangular plans (with 3m offset) aligned with the north axis, with 0% WWR on the north and south facades and 40% WWR on the east and west facades. However, Design Option 2.2 is made of two

perpendicular rectangular plans, one facing the north and the other to the east, with 20% WWR on the north and south facades and 40% WWR on the east and west facades. The roof is 4% slope in Design Options 2.1 and 2.3, while it is flat in Design Option 2.2. In Design Option 2.1, the U-value and Solar Heat Gain Coefficient (SHGC) of the glazing are 2.8372 W/m<sup>2</sup>K and 0.25, respectively. Those two parameters are assumed to be 0.6 W/m<sup>2</sup>K and 0.25 for Design Option 2.2 and same for Design Option 2.3. In Design Option 2.1, exterior walls, floors and roof are constructed of concrete with different thicknesses. In Design Options 2.2 and 2.3 the roof and the floors are identical to Design Option 2.1 while the exterior walls are made of Structurally Insulated Panels (SIP). The thermal properties of the material layers constructing a concrete block and an SIP construction are obtained from the literature [25], [91] and listed in Table 5-4.

**Table 5-4 Material thermal properties and deviations for test case 2.**

Wall Construction	Material layers	Thickness [m]		Thermal Conductivity [W/mK]		Density [kg/m <sup>3</sup> ]		Specific Heat Capacity [J/kg°K]	
		μ	σ	μ	σ	μ	σ	μ	σ
Structurally Insulated Panel (SIP)	Finishes - Interior - Plasterboard	0.012	0.0005	0.18	0.02	1030	135	970	85
	Wood - Stud Layer	0.02	0.002	0.2	0.2	648	254	1845	870

	Structure - Timber Insulated Panel - OSB	0.01	0.001	0.13	0.0075	545	20	1740	442.5
	Structure - Timber Insulated Panel - Insulation	0.09	0.005	0.046	0.0052	11	1	805	17.5
	Structure - Timber Insulated Panel - OSB	0.01	0.001	0.13	0.0075	545	20	1740	442.5
	Concrete: Sand/Cement Screed	0.21	0.021	1.13	0.10	2000	30	1000	106
<b>Concrete Blocks</b>	Finishes - Interior - Plasterboard	0.012	0.0005	0.18	0.02	1030	135	970	85
	Concrete	0.2	0.02	1.41	0.13	1900	28.5	1000	106

The four main parameters defining the thermal properties of a material for energy simulation are listed as thickness, thermal conductivity, density, and specific heat capacity

[98]. The thermal properties of each material are defined with a mean and a standard deviation value which are required to generate samples with normal distribution.

The SIP construction consists of several layers of materials including interior plasterboard, wood stud layer, timber insulated panel OSB and insulation, and concrete. The concrete block construction is made of a layer of interior plasterboard as the finishes and a layer of concrete as the structure of the construction.

Other system variables with uncertainties including the internal heat gain sources, the infiltration rate, and the ventilation rates are listed with the mean and standard deviation values in Table 5-5. The mean values are learned from the literature [86]; however, the standard deviations of all system variables are assumed to be equal to 10% of the corresponding mean values, due to a lack of information. This assumption is based on the previous research done by [90]. For the future research, it is encouraged to conduct experiments or use expert knowledge to provide an appropriate standard deviation for each input variable with respect to their specific characteristics in reality. For instance, the standard deviation for air flow may be higher than 10%, while the standard deviation for the glazing U-value may be lower than 10% in reality.

**Table 5-5 Description of the system’s design assumptions.**

<b>Variable [Unit]</b>	<b><math>\mu</math></b>	<b><math>\sigma</math></b>
<b>Equipment loads per area [W/m<sup>2</sup>]</b>	10.98	10%
<b>Infiltration (air flow) rate per area [m<sup>3</sup>/s-m<sup>2</sup>]</b>	0.0003	10%

<b>Lighting density per area [W/m<sup>2</sup>]</b>	9.36	10%
<b>Number of people per area [ppl/m<sup>2</sup>]</b>	0.25	10%
<b>Ventilation per area [m<sup>3</sup>/s-m<sup>2</sup>]</b>	0.0006	10%
<b>Ventilation per person [m<sup>3</sup>/s-m<sup>2</sup>]</b>	0.005	10%

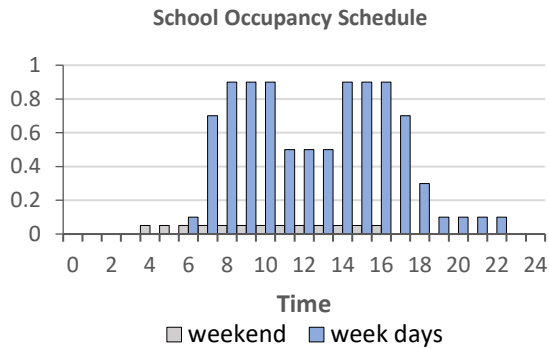
An ideal loads air system is used for all the thermal zones in the building. The ideal loads air system is an input object which provides a model for an ideal HVAC system. The object is modeled as an ideal VAV terminal unit with variable supply temperature and humidity. The supply air flow rate is varied between zero and the maximum in order to satisfy the zone heating or cooling load, zone humidity controls, outdoor air requirements, and other constraints, if specified [99].

In addition to the physical parameters, some deterministic system requirements are set as follows:

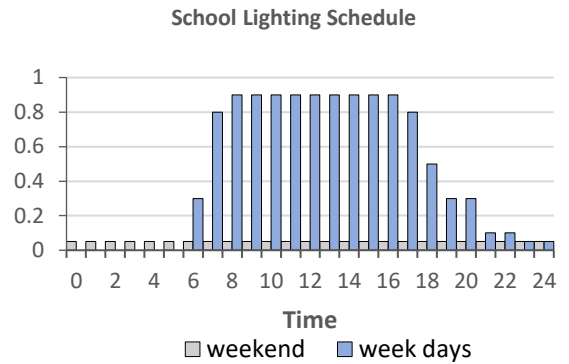
- $X_{det_1}$ : maximum heating supply air temperature: 40°C,
- $X_{det_2}$ : minimum cooling supply air temperature: 14°C,
- $X_{det_3}$ : maximum heating supply air humidity ratio: 0.008 kg-H<sub>2</sub>O/kg-air,
- $X_{det_4}$ : minimum cooling supply air humidity ratio: 0.0085 kg-H<sub>2</sub>O/kg-air,
- $X_{det_5}$ : recirculated air per area: 0 m<sup>3</sup>/s-m<sup>2</sup>.
- $X_{det_6}$ : Occupancy, lighting, and equipment schedules are matched with

the school schedules in the ASHRAE 90.1-2010 [100]. Figure 5-7 a) to c)

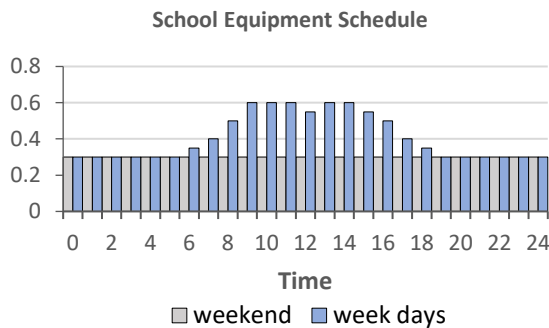
demonstrate the weekend and weekdays operation schedules for this test case.



**a) School occupancy schedule**



**b) School lighting schedule**



**c) School equipment schedule**

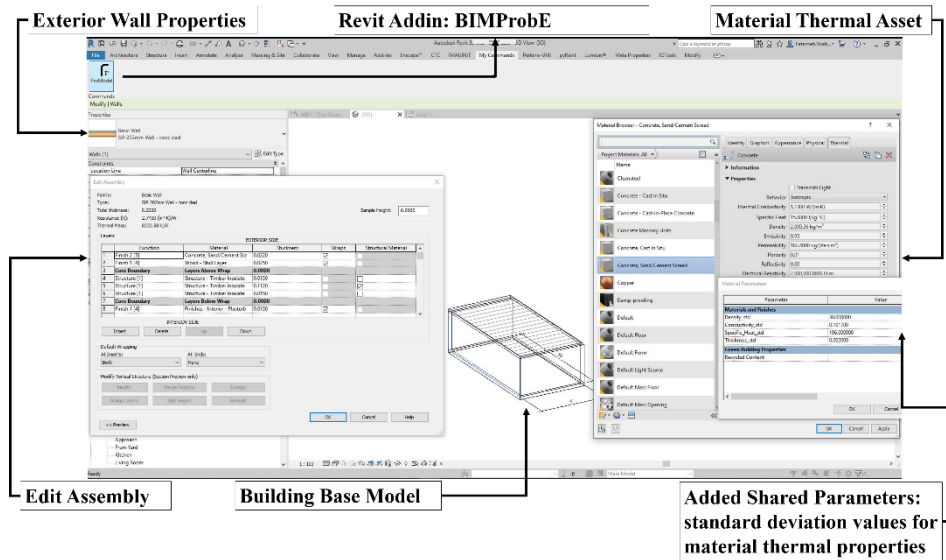
**Figure 5-7 The School operation schedules.**

The school weekday operations schedules follow different patterns than weekend schedules. For instance, Figure 5-7 a) the weekday occupancy schedule, shows a rise from 6 am to 8 am. Then, it stagnates until noon when it shows a decline in occupants’ presence, that is normally lunch time for most of the people. At around 2pm the occupancy rate goes up and stays fixed until 4 pm when it declines again. On the other hand, the weekend occupancy schedule only shows a fixed occupancy rate from 4am to 4pm.

### *Pre-processing*

The base model of the rectangular plan is built in Revit. The building elements including exterior walls, roof, and floor are modeled and the associated materials are assigned. To add the probability distributions to the thermal properties of building materials, a database was created in Microsoft Excel, based on the values learned from the literature [25], [91]. The dataset is a spreadsheet containing the mean and standard deviation of building materials' thickness, thermal conductivity, density, and specific heat capacity. The developed add-in for Revit helps create shared parameters to add probability distributions to the thermal properties of the materials and export this information to Excel. Figure 5-8 demonstrates the Revit model and the workflow to set the probability distributions for thermal properties of the building materials.





**Figure 5-8 BIMProbe addin developed for Revit.**

The parametric capabilities of Grasshopper in Rhino were used to create the three design options of the test case model. The WWR values were set in Grasshopper using the Honeybee glazing creator component. Also, internal heat gain sources, ventilation rates, infiltration rate, number of people, and building operation schedules were defined in Grasshopper using the Honeybee EnergyPlus zone loads component.

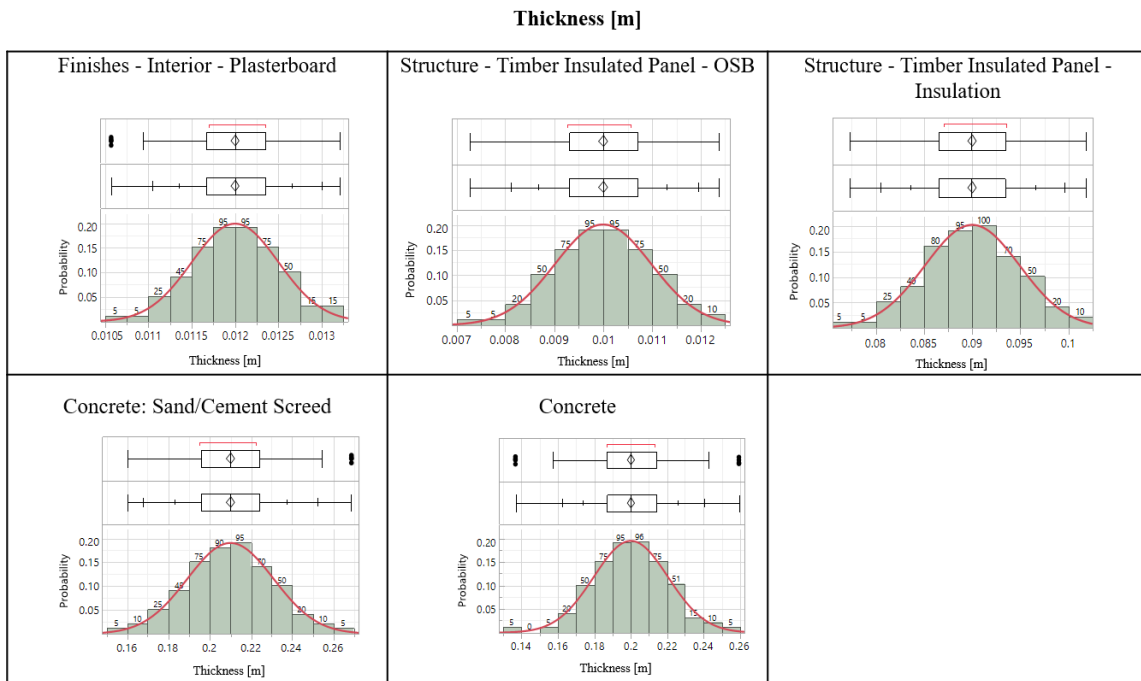
### *Sampling and Simulation*

In this test case, it is assumed that  $X_{uncer} = \{x_{uncer_1}, x_{uncer_2}, x_{uncer_3}, \dots, x_{uncer_k}\}$ ,  $k = 10$ . The ten input variables containing uncertainties include the four thermal properties of exterior walls (thickness ( $x_{uncer_1}$ ), conductivity ( $x_{uncer_2}$ ), specific heat capacity ( $x_{uncer_3}$ ), and density ( $x_{uncer_4}$ )), the three internal heat gain loads (equipment ( $x_{uncer_5}$ ), lighting ( $x_{uncer_6}$ ), and people loads ( $x_{uncer_7}$ )), the infiltration rate ( $x_{uncer_8}$ ), and the two

ventilation rate factors (ventilation per person ( $x_{uncer_9}$ ) and ventilation per area ( $x_{uncer_{10}}$ )) for which the mean and standard deviation values are obtained from the literature studies [25], [91]. The ten selected variables are known as the main sources of uncertainty in building energy simulation [3].

In this test case, the probability distributions of all input variables are set as normal or Gaussian if not fixed, since the variations take place due to unpredictable changes during construction, climate change, building age, and building maintenance.

In the probabilistic approach, for each parameter  $x_{uncer_i}$ , 500 samples are generated. For those variables with normal distribution,  $N(\mu_i, \sigma_i^2)$ , the samples were generated using Latin Hypercube Sampling (LHS) method. Figure 5-9 to Figure 5-13 depict the histograms, and box plots for each design variable with associated uncertainties. The mean and standard deviation for each material is used to create a normal probability distribution using Python programming in Grasshopper. The histograms, quantile box plots, and outlier box plots are generated with JMP to visualize the data.



**Figure 5-9 The probability distributions of the materials' thickness (test case 2).**

Figure 5-9 shows the probability distributions of thickness for five different layers of

material. These materials are constructing the two exterior wall types studied in this test

case. The Finishes - Interior – Plasterboard, Wood - Stud Layer, Structure - Timber

Insulated Panel – Insulation, Structure - Timber Insulated Panel – OSB, and concrete -

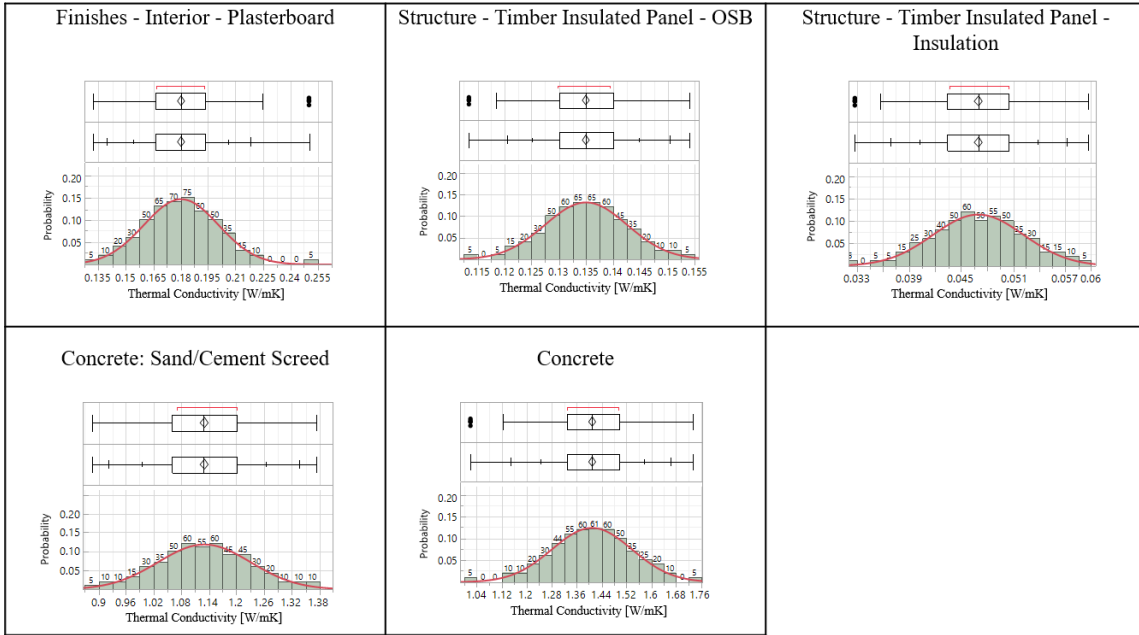
sand/cement screed construct the SIP wall type. The concrete and the Finishes - Interior

– Plasterboard layer make the concrete blocks. The thermal properties of each material

layer of the two wall types are listed in Table 5-4. The mean and standard deviation

values are obtained from the literature [22], [25], [91].

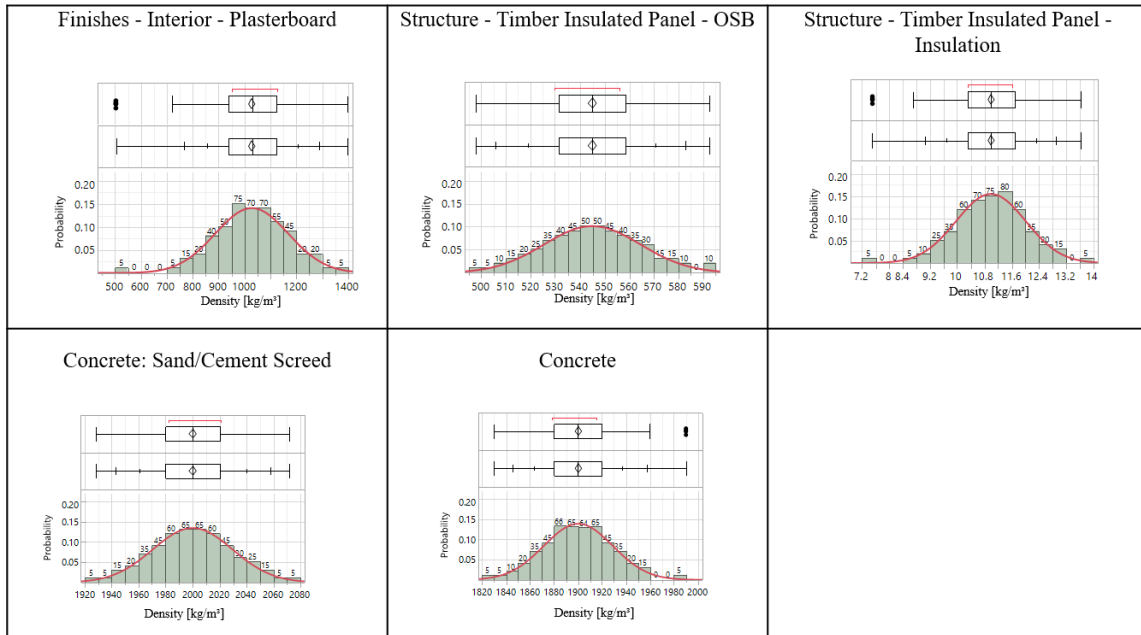
**Thermal Conductivity [W/mK]**



**Figure 5-10 The probability distributions of the materials' thermal conductivity (test case 2).**

Figure 5-10 demonstrates the probability distributions of thermal conductivity for five specific materials discussed above. The mean and standard deviation values are obtained from the literature [22], [25], [91].

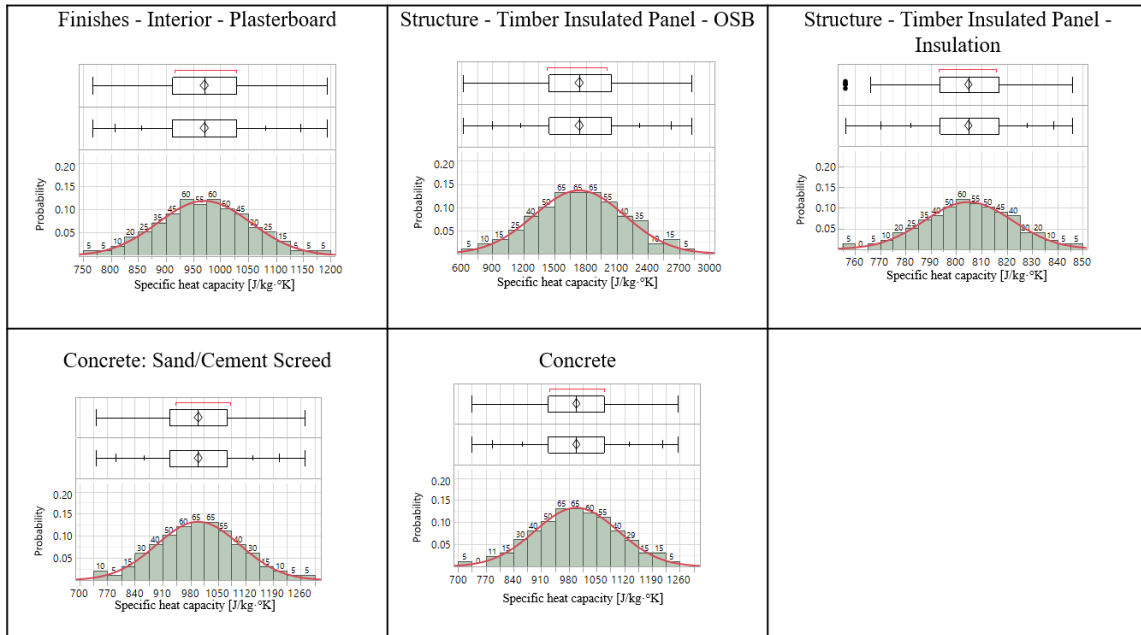
**Density [kg/m<sup>3</sup>]**



**Figure 5-11 The probability distributions of the materials' density (test case 2).**

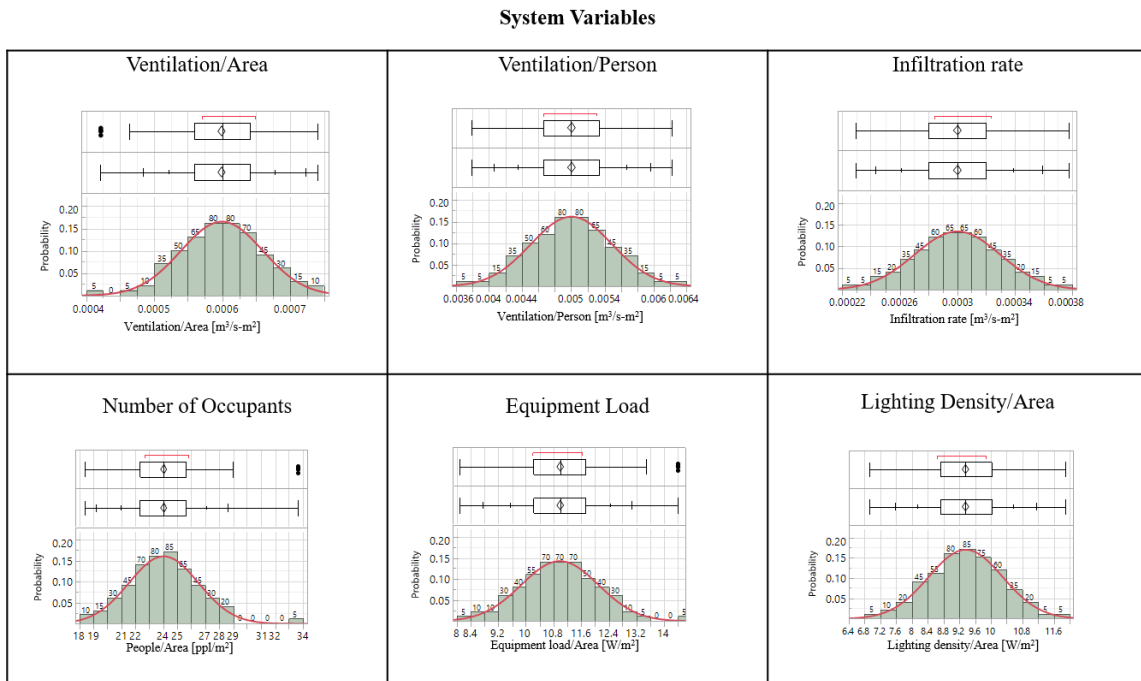
Figure 5-11 depicts the probability distributions of density for the five material layers discussed above. The mean and standard deviation values are obtained from the literature [22], [25], [91].

**Specific heat capacity [J/kg·K]**



**Figure 5-12 The probability distributions of the materials' specific heat capacity (test case 2).**

Figure 5-12 shows the probability distributions of specific heat capacity for the five materials discussed above. The mean and standard deviation values are obtained from the literature [22], [25], [91].



**Figure 5-13 The probability distributions of the system’s variable (test case 2).**

Figure 5-13 illustrates the probability distributions of system variables including ventilation per area, ventilation per person, infiltration rate, number of occupants, equipment load, and lighting density per area. The mean and standard deviation values are obtained from the literature [86], [90].

The mean and standard deviation of thermal properties of building materials, also some system requirements are obtained from the literature and set using the capabilities of BIM API. This information is exported to Excel, stored in Excel and used in Grasshopper to run parametric energy simulations (CPython and Numpy were used to select 500 random samples from the normal distribution). Using all the aforementioned design and system assumptions, 500 energy simulations are run for each design option and

the results are recorded. The software EnergyPlus (an energy simulation software) is used to run 500 energy simulations with the samples. For each run of the energy simulation, a corresponding value from the sample pool of each design variable ( $x_{uncer_i}$ ) is selected and inserted into the simulation model, and as a result, 500 output values are obtained. The set of outcomes whose elements correspond to the samples are  $Y = \{y_1, y_2, y_3, \dots, y_m\}$ ,  $m = 500$ , where  $Y$  denotes the space of output values.

On the other hand, in the deterministic approach, all design parameters ( $x_i$ ), regardless of being deterministic or uncertain, are assigned to their associated mean ( $\mu_i$ ) as a fixed value ( $x_i = \mu_i$ ). Fixing all the input parameters at their mean values, the energy simulation is run once and a single output  $y_{det} = f(\mu_1, \mu_2, \mu_3, \dots, \mu_n)$ , is obtained, where ( $\mu_1, \mu_2, \mu_3, \dots, \mu_n$ ) are the means of the design variables.

### *Post-Processing*

The simulation results are collected and studied to compare the design options. The output results are represented by the values of deterministic and probabilistic outputs. The probabilistic results include mean, standard deviation, and variance. The mean value shows the average of the sample, while standard deviation and variance are presented as additional measures of risk. In addition, design options are ranked according to the criteria of expected value, maximax, and maximin. The results are thoroughly discussed in the next chapter (chapter 6).



## **5.5 Test Case 3 (TC3-IL)**

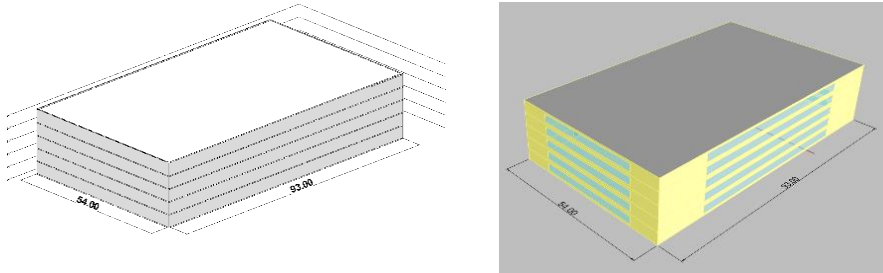
This test case studies the energy performance of a hypothetical mid-size office building with three design options in the first phase. In the second phase, a new design option is designed and compared with the best ranked design option across the three. A higher level of complexity in the occupant behavior in office spaces allows the implementation of different types of probability distributions, including normal and Poisson distributions. Based on the findings of (Zhou et al., 2015) the input variables related to occupant behavior or presence can be best described with Poisson distributions.

This test case compares three proposed design options using deterministic and probabilistic methods to identify the best design option in terms of building energy performance. The results obtained from the deterministic method are compared with the probabilistic results.

### **5.5.1 Test Case 3 (TC3-IL) Model**

This test case presents a 5-story office building, 54m by 93m (Total gross area of 25,110 m<sup>2</sup>). Figure 5-14 (a), (b), and (c) show the 3D view of the building base model in Revit, Rhino, and the building elements and zones visualization in Rhino using Ladybug tools in Grasshopper, from left to right. The building geometry is created in Revit and the materials are defined in the same model. The building information including the materials' thermal properties is exported from Revit to Excel. This information is used in

Rhino/Grasshopper to generate samples and run multiple energy simulations using the parametric capabilities of Grasshopper.



**Figure 5-14 The geometric representation of test case 3 (Revit model on the left and Rhino model on the right).**

This test case consists of two separate phases. In the first phase, three design options (Design Options 3.1, 3.2, and 3.3) are compared to find the best thermal energy consumption. In the second phase, a new design option (Design Option 3.4) is developed to be compared against the best design option among the first three. The building geometry, layout, orientation, operation schedules, internal heat gain sources, and HVAC type are assumed to be identical throughout this experiment. On the other hand, exterior wall construction, floor construction, roof construction, Window-to-Wall Ratio (WWR), glazing properties, and temperature set points vary among the proposed design options (See Table 5-6, Table 5-8, Table 5-9, and Table 5-10). Table 5-6 presents the materials' specifications of Design Options 3.1, 3.2, and 3.3.

**Table 5-6 Test case 3, phase 1 design variable assumptions.**

<b>Variable [Unit]</b>	<b>Design Option 3.1</b>	<b>Design Option 3.2</b>	<b>Design Option 3.3</b>
<b>Exterior wall construction</b>	Steel Framed; R-21.0 (RSI value = 3.7 m <sup>2</sup> K/W);	Steel Framed; R-13.0 + 7.5 CI (RSI value = 2.76 m <sup>2</sup> K/W);	Steel Framed; R-19.0 batt 2 in. CI Metal Z-girts (RSI value = 3.35 m <sup>2</sup> K/W);
<b>Floor construction</b>	Steel Joist; R-30.0 (RSI value = 4.59 m <sup>2</sup> K/W);	Steel Joist; R-30.0 (RSI value = 4.59 m <sup>2</sup> K/W);	Steel Joist; R-30.0 (RSI value = 4.59 m <sup>2</sup> K/W);
<b>Roof construction</b>	High Performance Roof-8" concrete 6 in. CI (RSI value = 5.88 m <sup>2</sup> K/W);	Insulation Entirely above Deck; R-20.0 CI (RSI value = 4.17 m <sup>2</sup> K/W);	High Performance Roof-8" concrete 6 in. CI (RSI value = 5.88 m <sup>2</sup> K/W);
<b>Window to Wall Ratio (WWR)%</b>	70/65/60/20 (N/S/E/W)	40 building overall	50/70/40/45 (N/S/E/W)
<b>Glazing</b>	U=1.7 W/m <sup>2</sup> K (0.3 Btu/hr-ft <sup>2</sup> -°F)	U=3.12 W/m <sup>2</sup> K (0.55 Btu/hr-ft <sup>2</sup> -°F)	U=1.2 W/m <sup>2</sup> K (0.3 Btu/hr-ft <sup>2</sup> -°F)
<b>Glazing SHGC</b>	0.20	0.42	0.20

Table 5-6 indicates the value assumptions for the thermal properties of building materials, including exterior walls, floors, roof, and glazing. The materials in this test case are specified with some attributes such as RSI value and U-value. These terms are commonly used in the building industry to describe the thermal resistance and thermal conductivity of building materials. The mean values of these variables are defined based on the ASHRAE 90.1-2010 requirements for this test case's climate zone (5A). In this test case, the RSI Values of building elements, including wall assemblies, and floor and roof constructions are set through the thermal properties of building materials. A database was created in Microsoft Excel to define the corresponding materials thickness and thermal conductivity to obtain the desired RSI value for the building elements based on the ASHRAE 90.1-2010 recommendations and typical building construction in this climate zone (5A). A set of different exterior wall assemblies are defined with RSI Values and

corresponding thickness and thermal conductivity values. The same pattern is taken for the floor and roof construction types. In this test case the samples of RSI value are generated by dividing the samples of material thickness by the samples of thermal conductivity. The probability distribution of the building element's thickness is obtained from the literature review, and the probability distribution of thermal conductivity is calculated having the mean values of thickness and RSI Value. The standard deviation for thermal conductivity, however, is set to 10% due to a lack of information. de Wit (2001) has estimated this percentage to be up to 10% in his report [90], pages 181-184.

The minimum requirements specified by the ASHRAE 90.1-2010 for this specific climate zone (5A) are presented in the Design Option 3.2:

- The RSI Values of the opaque materials are recommended to be 2.76 m<sup>2</sup>K/W for the exterior walls, 4.59 m<sup>2</sup>K/W for the floor construction, and 4.17 m<sup>2</sup>K/W for the roof construction.
- The window to wall ratio (WWR) is 40% for the building overall.
- The glazing is specified with the u-value of 3.12 W/m<sup>2</sup>K, the solar heat gain coefficient (SHGC) of 0.42, and Visible Transmittance (VT) of 0.76.

The design variables are altered from the ASHRAE baseline in Design Options 3.1, and 3.3 to compare building energy performance. For instance, the RSI value of the exterior wall is increased to 3.35 m<sup>2</sup>K/W (Design Option 3.3) and 3.7 m<sup>2</sup>K/W (Design Option 3.1).

The internal heat gain loads, ventilation rates, and infiltration rate, along with the HVAC system description and building operation schedules are used to convert the building mass into thermal zones. The realizations of the mean values for the internal heat gain loads, ventilation rates, and infiltration rate for all three design options in the first phase and the fourth design option in the second phase, are specified based on the ASHRAE 90.1-2010 requirements for climate zone 5A (Table 5-7).

**Table 5-7 Description of the system’s design assumptions.**

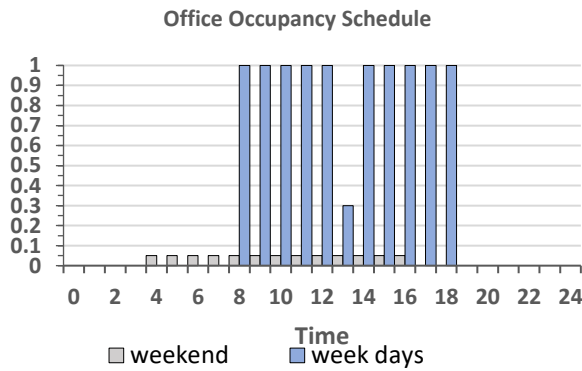
<b>Variable [Unit]</b>	<b><math>\mu</math></b>	<b><math>\sigma</math></b>
<b>Equipment loads per area [W/m<sup>2</sup>]</b>	10.765	10%
<b>Infiltration (air flow) rate per area [m<sup>3</sup>/s-m<sup>2</sup>]</b>	0.0003	10%
<b>Lighting density per area [W/m<sup>2</sup>]</b>	10.55	10%
<b>Number of people per area [ppl/m<sup>2</sup>]</b>	0.07	10%
<b>Ventilation per area [m<sup>3</sup>/s-m<sup>2</sup>]</b>	0.0006	10%
<b>Ventilation per person [m<sup>3</sup>/s-m<sup>2</sup>]</b>	0.005	10%

Similar to test case 2, the standard deviations of all system variables are assumed to be equal to 10% of the corresponding mean values, due to a lack of information. This assumption is based on the previous research done by [90]. de Wit (2001) has estimated this percentage to be up to 10% in his report [90], pages 181-184.

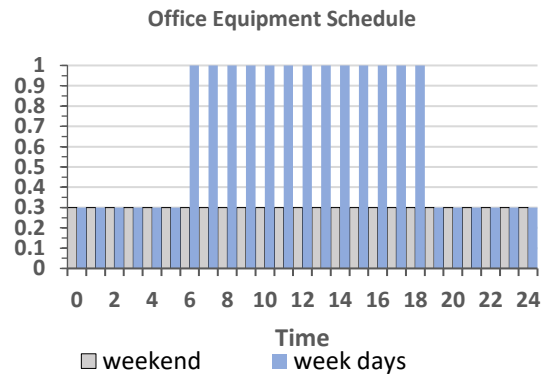
Some of the HVAC system requirements are assumed to be deterministic and set as follows:

- $X_{det_1}$ : Maximum heating supply air temperature: 40°C,
- $X_{det_2}$ : minimum cooling supply air temperature: 14°C,
- $X_{det_3}$ : maximum heating supply air humidity ratio: 0.008 kg-H<sub>2</sub>O/kg-air,
- $X_{det_4}$ : minimum cooling supply air humidity ratio: 0.0085 kg-H<sub>2</sub>O/kg-air,
- $X_{det_5}$ : recirculated air per area: 0 m<sup>3</sup>/s-m<sup>2</sup>.
- $X_{det_6}$ : Occupancy, lighting, and equipment schedules are matched with

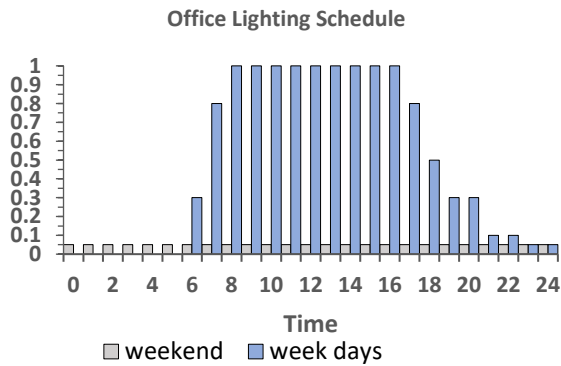
the office schedules in the ASHRAE 90.1-2010 [100]. Figure 5-15 demonstrate the weekend and weekdays operation schedules for this test case.



a) Office occupancy schedule.



b) Office equipment schedule.



c) **Office lighting schedule.**

**Figure 5-15 The office operation schedules.**

The office weekday operation schedules show different patterns than the weekend schedules. However, unlike the school and residential schedules, the office schedules show less variations throughout the office hours.

The HVAC parameters for Design Option 3.2 are defined as suggested by the ASHRAE 90.1-2010. Some of the HVAC parameters for the other proposed design options are assumed to be the same as Design Option 3.2, but others are assumed to be different from the ASHRAE 90.1-2010 baseline requirements as detailed in Table 5-8. from the Block87)

**Table 5-8 Test case 3, phase 1, description of the system specifications.**

<b>Variable [Unit]</b>	<b>Design Option 3.1</b>	<b>Design Option 3.2 (ASHRAE 90.1- 2010 Baseline)</b>	<b>Design Option 3.3</b>
<b>Zone design conditions</b>	23°C Cooling/21°C Heating; no active RH control at zone.	23°C Cooling/21°C Heating; no active RH control at zone.	23°C Cooling/21°C Heating; no active RH control at zone.
<b>System type</b>	VAV w/Reheat.	VAV w/Reheat	VAV w/Reheat.
<b>Supply air temperature</b>	12.78°C Cooling/32.2°C	12.2°C Cooling/32.2°C	12.78°C Cooling/32.2°C

	Heating; -15°C reset based on warmest zone.	Heating; -15°C reset based on warmest zone.	Heating; -15°C reset based on warmest zone.
<b>Chilled water temperature</b>	7.2°C Supply   16°C Return Reset based on load.	6.7°C Supply   13°C Return Reset based on outside air.	7.2°C Supply   16°C Return Reset based on load.
<b>Hot water temperature</b>	60°C Supply   43°C Return Reset based on load.	82.2°C Supply   54°C Return Reset based on outside air.	60°C Supply   43°C Return Reset based on load.

The HVAC system type is assumed to be variable air volume (VAV) with Reheat for all the four design options. This type of HVAC provides conditioned air to each thermal zone at the set point temperature. The temperature set points are defined to be 23°C for cooling and 21°C for heating. The supply air temperature for cooling is set as 12.78°C for Design Options 3.1, and 3.3, and 12.2°C for Design Option 3.2. This temperature is set to 32.2°C for heating for all design options. The chilled water temperature is set to 7.2°C for Design Options 3.1 and 3.3, and 6.7°C for Design Option 3.2. The hot water temperature is set to 60°C for Design Options 3.1 and 3.3, and 82.2°C for Design Option 3.2.

In the second phase of this experiment, a new design option named as Design Option 3.4 is developed to be compared to the best design option among the first three.



Table 5-9 shows the building material assumptions for Design Option 3.4, developed in test case3, phase 2.

**Table 5-9 Test case 3, phase 2 design variable assumptions (Design Option 3.4).**

<b>Variable [Unit]</b>	<b>Design Option 3.4</b>
<b>Exterior wall construction</b>	Steel Framed; R-19.0 batt 2 in. CI Metal Z-girts (RSI value = 3.35 m <sup>2</sup> K/W);
<b>Floor construction</b>	Steel Joist; R-19.0 (RSI value = 3.35 m <sup>2</sup> K/W);
<b>Roof construction</b>	High Performance Roof-8” concrete 6 in. CI (RSI value = 5.88 m <sup>2</sup> K/W);
<b>Window to Wall Ratio (WWR)%</b>	50/70/40/45 (N/S/E/W)
<b>Glazing</b>	U=1.2 W/m <sup>2</sup> K (0.3 Btu/hr-ft <sup>2</sup> -°F)
<b>Glazing SHGC</b>	0.15

The system design variables for Design Option 3.4 are described in Table 5-10.

**Table 5-10 Test case 3, phase 2 description of the system specifications (Design Option 3.4).**

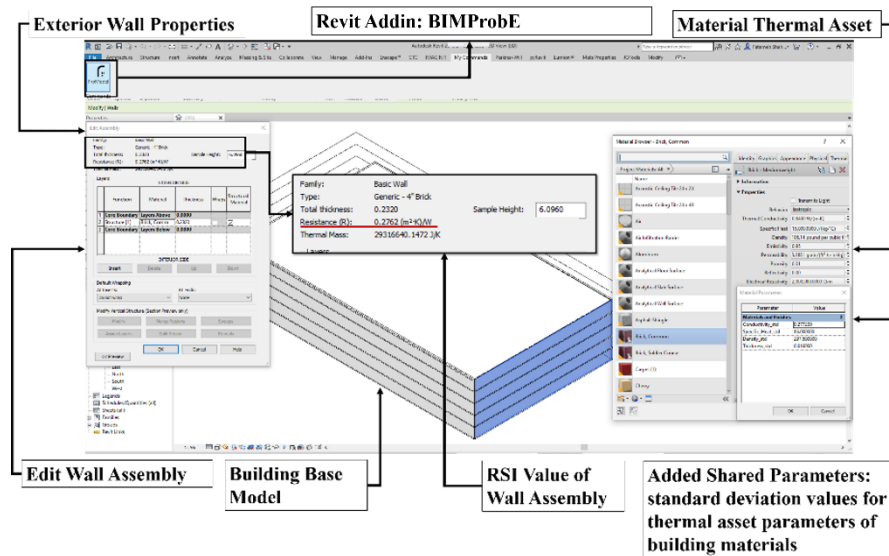
<b>Variable [Unit]</b>	<b>Design Option 3.4</b>
<b>Zone design conditions</b>	23°C Cooling/21°C Heating; no active Reheat control at zone.

<b>System type</b>	VAV w/Reheat.
<b>Supply air temperature</b>	12.78°C Cooling/32.2°C Heating; -15°C reset based on warmest zone.
<b>Chilled water temperature</b>	6.7°C Supply   13°C Return Reset based on outside air.
<b>Hot water temperature</b>	82.2°C Supply   54°C Return Reset based on outside air.

The other design variables including operation schedules, and the system's design assumptions of Design Option 3.4 is the same as the first three design options.

#### *Pre-Processing*

The building element modeling environment in Revit is used to model the building. The same workflow as used in test case 2 is followed to model the building elements, assign the associated materials, and add the probability distributions to the thermal properties of building materials. The developed add-in for Revit allows creating required shared parameters to add probability distributions of the thermal properties of building materials and export this information to Excel for further analysis. Figure 5-16 demonstrates the Revit model and the workflow to set the probability distributions for thermal properties of building materials.



**Figure 5-16 The new BIM API add-in for getting and setting the probability distributions of thermal properties for building materials and exporting the RSI Values (test case 3).**

The visual programming tool in Rhino, Grasshopper, is used to develop three different design options in the first phase and the fourth design option in the second phase of this analysis. The two phases represent an example of design option generation and evaluation in terms of improving building performance and create different scenarios to demonstrate the applications of probabilistic methods versus deterministic method. The building mass was converted to thermal zones in each case with defining the adjacency types, WWRs, internal heat gain loads, and HVAC systems.

### *Sampling and Simulation*

The design parameters with uncertainties are denoted as  $X_{uncer} = \{x_{uncer_1}, x_{uncer_2}, x_{uncer_3}, \dots, x_{uncer_k}\}$ ,  $k = 11$ . In this test case, the eleven input variables

with uncertainties include the RSI values of exterior walls, the glazing U-value, the RSI Values of floor construction, the RSI Values of roof constructions, the three internal heat gain loads (equipment ( $x_{uncer_5}$ ), lighting ( $x_{uncer_6}$ ), and people loads ( $x_{uncer_7}$ )), the infiltration rate ( $x_{uncer_8}$ ), the two ventilation rate factors (ventilation per person ( $x_{uncer_9}$ ) and ventilation per area ( $x_{uncer_{10}}$ )), and the infiltration schedule that is strongly correlated with the possibility of opening or closing windows by occupants ( $x_{uncer_{11}}$ ) for which the mean and standard deviation values are obtained from the literature studies [25], [91].

The occupant behavior in the opening and closing windows is defined based on the Outdoor Air Temperature (OAT) and is connected to the infiltration schedule. This variable is studied through the possibility of opening the windows when the outdoor air temperature (OAT) reaches a certain point. For example, if OAT is higher than 20°C (with 0.2°C variation), the users would probably open the windows. This probability status is recorded throughout the year as zeros and ones (for closing and opening the windows). This list of zeros and ones is saved as an Excel file, and the Excel file is linked to the infiltration schedule, which is used in the EnergyPlus simulations.

In the probabilistic approach, for each parameter  $x_{uncer_i}$ , 500 samples are generated. For those variables with normal distribution,  $N(\mu_i, \sigma_i^2)$ , including the physical parameters of materials, ventilation rate factors, and infiltration rate, the samples were generated using Latin Hypercube Sampling (LHS) method, while other variables were sampled using the Poisson distribution. Figure 5-17 to Figure 5-20 demonstrate the histograms, quantile box plots, and outlier box plots of the input sample sets.

RSI values

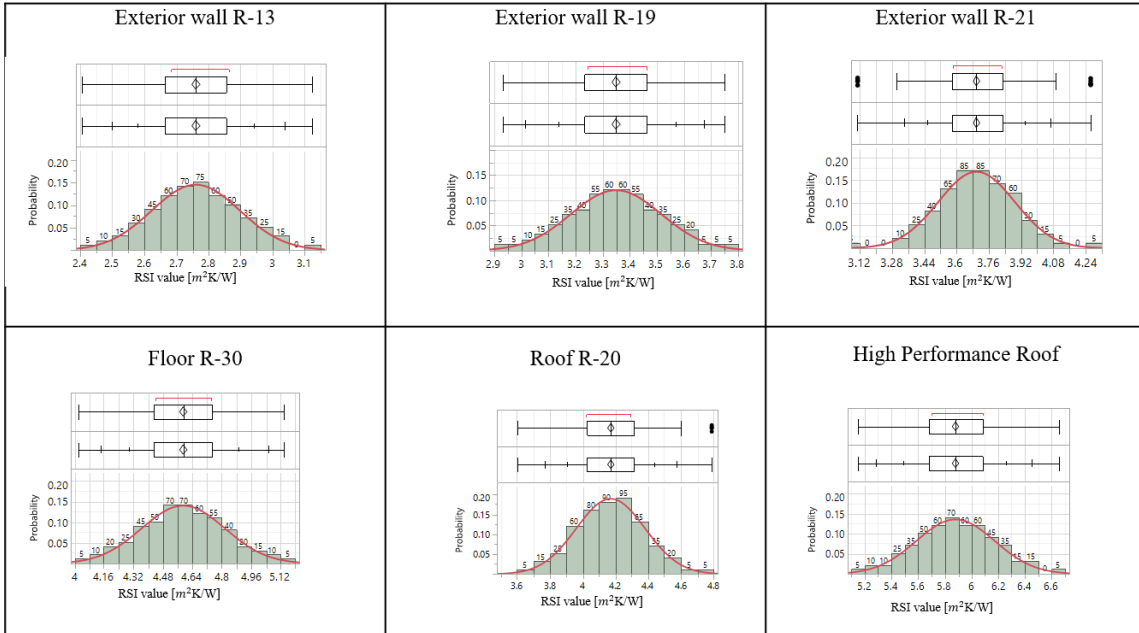


Figure 5-17 The probability distributions of RSI Values for exterior walls, floor construction, and roof constructions (test case 3).

Glazing U-value

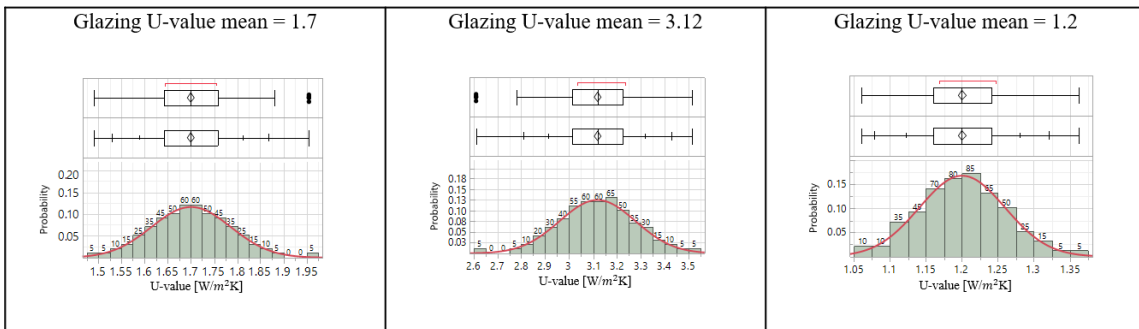
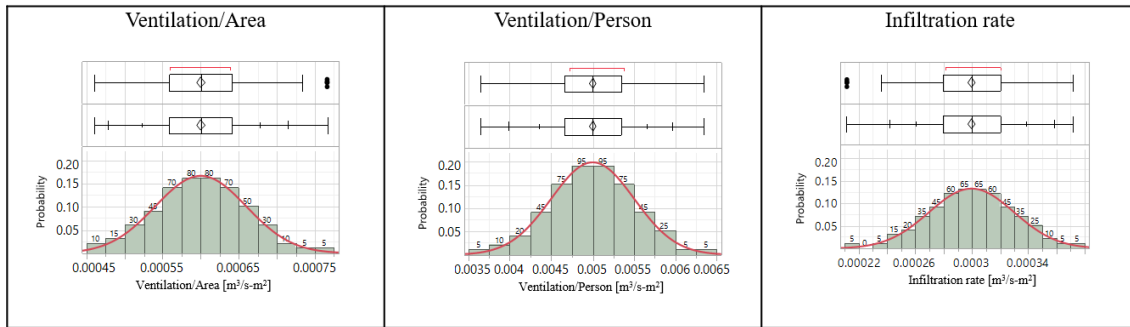


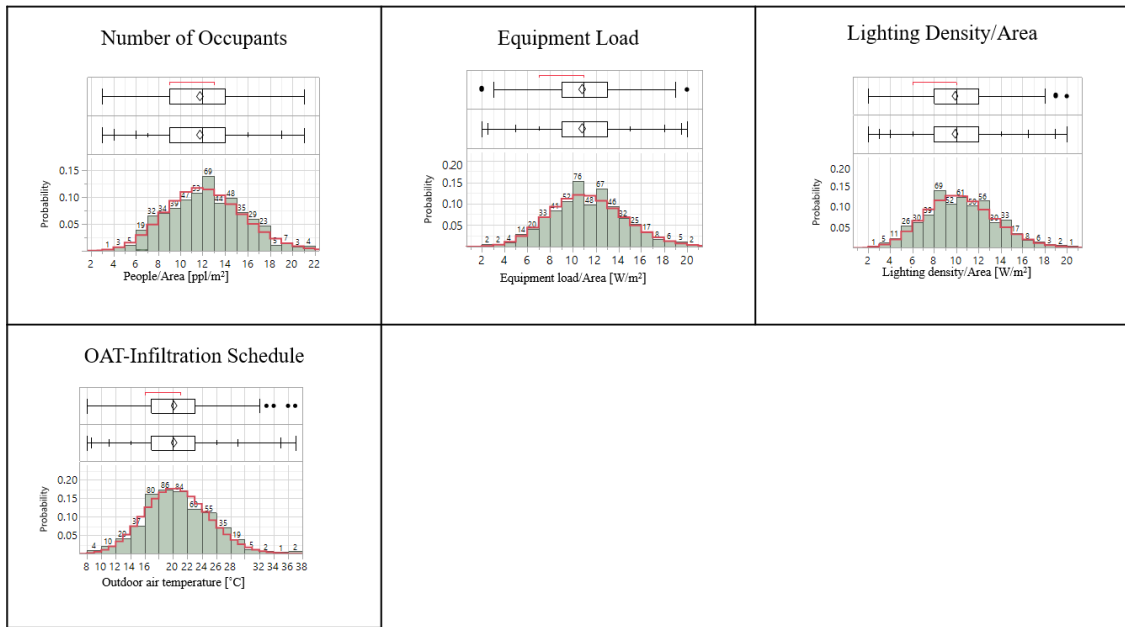
Figure 5-18 The probability distributions of U-values for the glazing (test case 3).

### System Variables



**Figure 5-19 The probability distributions of system variables (test case 3).**

Figure 5-17 depicts the probability distributions of RSI values for three wall types, a floor type, and two roof types. Figure 5-18 shows the probability distributions of U-value for three different glazing types. Figure 5-19 illustrates the probability distributions of system variables including ventilation per area, ventilation per person and infiltration rate. The mean values are defined based on the ASHRAE 90.1-2010 recommendations and the common practice in this climate zone (5A). The standard deviation is set to 5% for all the variables and 500 samples with normal distribution are generated using the LHS method.



**Figure 5-20 The probability distributions of internal heat gain loads and outdoor air temperature (test case 3).**

Figure 5-20 shows the probability distributions of internal heat loads and outdoor air temperature that affects the possibility of opening or closing the windows by the occupants. Those variables are described with Poisson distributions.

In this test case, the probability distributions of physical input variables  $\{x_{uncer_1}, x_{uncer_2}, x_{uncer_3}, \dots, x_{uncer_k}\}$ , also  $(x_{uncer_8})$ ,  $(x_{uncer_9})$ , and  $(x_{uncer_{10}})$  are set as normal or Gaussian since the variations take place due to unpredictable changes during construction, climate change, age, and maintenance. Other input parameters including  $(x_{uncer_5})$ ,  $(x_{uncer_6})$ , and  $(x_{uncer_7})$  are defined with the Poisson distributions. Bases on the findings of [95] the input variables related to occupant behavior or presence can be best described with Poisson distributions. The internal heat gain loads caused by the equipment

( $x_{uncer_5}$ ), lightings ( $x_{uncer_6}$ ), and occupants ( $x_{uncer_7}$ ), also the infiltration schedule ( $x_{uncer_{11}}$ ) are assumed to be highly dependent on the occupant presence, thus sampled using the Poisson distribution.

The building materials are defined in Revit and the information is stored in Excel and used in Grasshopper to run parametric energy simulations (CPython and Numpy are used to generate the samples). As described in the previous section, some variables are sampled from normal distributions while others are sampled from Poisson distributions. Similar to the previous test case (TC2\_CA), 500 energy simulations are run for each design option and the results were recorded in Excel. The software EnergyPlus (an energy simulation software) is used to run 500 energy simulations with the samples. For each run of the energy simulation, a corresponding value from the sample pool of each design variable ( $x_{uncer_i}$ ) is selected and inserted into the simulation model, and as a result, 500 output values are obtained. The set of outcomes whose elements correspond to the samples are  $Y = \{y_1, y_2, y_3, \dots, y_m\}$ ,  $m = 500$ , where Y denotes the space of output values.

The deterministic approach is identical to test case 2 (TC2\_CA): All the design parameters ( $x_i$ ), regardless of being deterministic or uncertain, are assigned to their associated mean ( $\mu_i$ ) as a fixed value ( $x_i = \mu_i$ ). Fixing all the input parameters at their mean values, the energy simulation is run once and a single output  $y_{det} = f(\mu_1, \mu_2, \mu_3, \dots, \mu_n)$  is obtained, where ( $\mu_1, \mu_2, \mu_3, \dots, \mu_n$ ) are the means of the design variables.



### *Post-Processing*

The simulation results are discussed similar to test case 2 (TC2\_CA). The results are thoroughly discussed in the next chapter.

## **5.6 Summary**

This chapter presented three test cases to validate the usability of the proposed framework (initial and advanced). The proposed probabilistic framework considers several sources of uncertainty in the process of building energy performance evaluation. Initially, the capabilities of Revit and the visual programming tool, Dynamo, were deployed to export the building information to Excel. A customized building energy calculator was developed in Excel to collect the building information and calculate the energy consumption. The mean values of the input parameters were obtained from Revit and the standard deviation values were entered manually. A normal probability distribution was created for each parameter and the values were inserted into the calculation iteratively. The results were recorded, and the probability distribution of the outputs was reported as the result of the probabilistic analysis. In the advanced framework, the BIM tools and BIM API are used to create probability distributions of material thermal properties for the building design options. This information is combined with other uncertainties related to building internal heat loads, HVAC input parameters, and occupant behavior, to predict the probability distribution of building annual thermal load.

The proposed framework is tested with three energy evaluation test cases, a

hypothetical residential unit in College Station, Texas, a hypothetical modular classroom design scenario in Los Angeles, California, and a hypothetical office building in Chicago, Illinois. The building annual thermal loads are compared for different design options using deterministic and probabilistic methods. The results are discussed in the next chapter.

## CHAPTER 6

### RESULTS AND DISCUSSION

This research has introduced a framework to incorporate probabilistic models into the building design decision making, demonstrated with three building design test cases. The ultimate goal of this research is to tackle data uncertainties and potential risks in architectural design decision-making with a focus on building energy performance. For that purpose, the results obtained from the proposed probabilistic framework are compared with those from the conventional deterministic method. Also, three design decision making criteria including expected value (the mean value), maximax (maximizes the maximum payoff available), and maximin (maximizes the minimum payoff achievable) are applied to discuss the simulation results based on different attitudes towards risk.

Two metrics are introduced including the key performance indicators (KPI) predicted by deterministic method, and the key risk indicators (KRI) [57] predicted by the probabilistic method. While KPI presents a measure of design objective, KRI shows the potential risks threatening the design objective [56]. In this research, the main design objective is improving building energy performance, thus KPI and KRI are defined to rank the predicted energy performance of different design options. KPI in this study is building annual thermal (heating and cooling) load, and the lower would be desired. KRIs include the mean, standard deviation, and variance of building annual thermal load. The probabilistic framework works with quantifying the uncertainties in design inputs and

allows predicting the probability distribution of the simulation outcome and the risks threatening building energy performance.

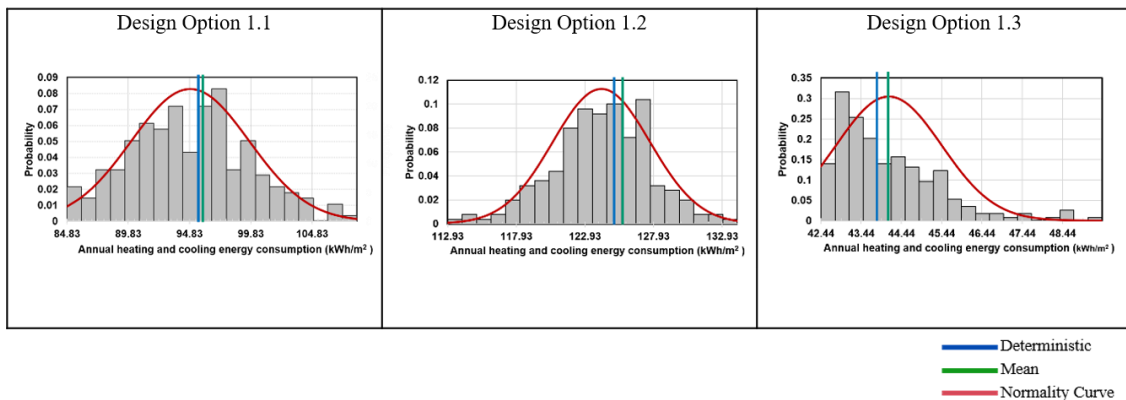
The result of this study confirms that probabilistic building performance analysis versus deterministic models provides important information about the consequences of design decisions under different possible conditions. The KRIs in addition to the predicted KPI may change the ranking order of design options and affect design decision making. This framework can be widely applied to other design problems and domains to enhance the process of design decision-making. This chapter discusses the results obtained from the three test cases described in Chapter 5.

### **6.1 Test Case 1 (TC1-TX) Results and Discussion**

This test case is obtained from a previous work done by the author to study the uncertainty propagation of building energy models. A full description of the work could be found in [85]. The initial framework (described in Chapter 4) is applied to compare the probability distribution of annual thermal load for three design options described in Chapter 5. Revit and Dynamo are used to create the building model and define the mean values of design input parameters. An energy calculator developed in Microsoft Excel is used to insert the probability distribution of the input parameters and estimate the KPI and KRIs. In the deterministic method, only the mean values of the input parameters  $E(X)$  are used to run energy simulations and a single output  $f(E(X))$  is obtained for each design option, where  $f(x)$  is the thermal energy calculation function. On the other hand, the probabilistic method creates a pool of 200 samples from a normal distribution for each

design option. The samples are inserted into the energy calculator and the outputs are recorded for uncertainty analysis and risk assessment.

In this test case, the results are visualized in Excel. Figure 6-1 illustrates the deterministic and probabilistic results of the annual thermal loads (kWh/m<sup>2</sup>) for each design option.



**Figure 6-1 Simulation results in terms of building annual thermal load by three design options of test case 1.**

In Figure 6-1, the deterministic results indicated by KPI for each design option is shown by a blue vertical line, the probabilistic results are illustrated by the relative frequency histograms with gray bars, and the mean values by the green lines. The red curved lines in Figure 6-1 suggest the fitness of normal probability distribution for the results. Note that normal distribution curves match the building thermal loads frequency histograms to some extent in Design Options 1.1 and 1.2.

The summary of the results for each design option is described as follows:

1) Design Option 1.1 shows a range of expected annual thermal load from 84.82 kWh/m<sup>2</sup> to 108.47 kWh/m<sup>2</sup> with a mean value of 94.87 kWh/m<sup>2</sup>. The standard deviation and variance of the result for Design Option 1.1 are 4.82 (kWh/m<sup>2</sup>) and 23.23 (kWh/m<sup>2</sup>)<sup>2</sup>, respectively. The deterministic method predicts a building annual thermal load equal to 95.33 kWh/m<sup>2</sup>, which is close to the mean value.

2) Design Option 1.2 shows a range of thermal load from 112.93 kWh/m<sup>2</sup> to 134.02 kWh/m<sup>2</sup> with a mean value of 124.14 kWh/m<sup>2</sup>. The standard deviation and variance of the result for Design Option 1.2 are 3.54 (kWh/m<sup>2</sup>) and 12.53 (kWh/m<sup>2</sup>)<sup>2</sup>, respectively. The deterministic result is equal to 123.93 kWh/m<sup>2</sup>, that is close to the mean value.

3) Design Option 1.3 shows a range of thermal load from 42.43 kWh/m<sup>2</sup> to 49.41 kWh/m<sup>2</sup>, with a mean value of 44.12 kWh/m<sup>2</sup>. The standard deviation and variance of the result for Design Option 1.3 are 1.19 (kWh/m<sup>2</sup>) and 1.71 (kWh/m<sup>2</sup>)<sup>2</sup>, respectively. The deterministic result shows the value of 43.88 kWh/m<sup>2</sup>, that is close to the mean value.

In this experiment, the performance ranking order of design options are matching between deterministic and probabilistic results. Based on the expected value decision making criterion, Design Option 1.3 has the best performance, Design Option 1.1 stands as the next option, and Design Option 1.2 shows the worst predicted thermal energy performance.

Other decision-making criteria including maximax and maximin allow designers to compare design options from an optimistic and a semi-pessimistic point of view,

respectively. Table 6-1 lists the maximum and minimum predicted values of thermal load for each design option.

**Table 6-1 Building thermal load under specific probability for test case 1.**

	<b>Minimum thermal load (kWh/m<sup>2</sup>)</b>	<b>Maximum thermal load (kWh/m<sup>2</sup>)</b>
<b>Design Option 1.1</b>	84.82	108.47
<b>Design Option 1.2</b>	112.93	134.02
<b>Design Option 1.3</b>	42.43	49.41

According to Table 6-1, the minimum and maximum thermal loads predicted for Design Option 1.3 are the lowest (42.43 kWh/m<sup>2</sup> and 49.41 kWh/m<sup>2</sup>, respectively). Therefore, Design Option 1.3 is confirmed to have the best performance, based on the maximax and maximin criteria. The maximax and maximin analyses led to the same ranking of the design options in thermal loads in this specific test case as using deterministic and probabilistic methods. This means that the use of probabilistic method in this specific test case does not show any added value to the design decision making. However, this test case provided a prototype framework that can be further utilized to investigate the probabilistic method, as will be shown in test cases 2 and 3.

In addition, the innovation of the initial framework is the mapping between Building Information Modeling (BIM) and probabilistic analysis methods. However, one of the limitations of this work was that the user would be required to input the standard deviation values of design inputs into the Excel GUI, manually. In the next phase of this research, shown by test cases 2 and 3, a database of building material parameters with a mean and a standard deviation for each parameter is constructed and accessible in the

building model. The developed database, also C# programming in BIM API allowed the development of a plugin for Revit to use the capabilities of this information rich platform to access the mean and standard deviation values of the building materials for probabilistic energy analysis. Furthermore, the visualization and analysis of the data would require a more comprehensive tool than Excel to deliver as much information as possible from the simulation outputs. A statistical software tool, known as JMP is used in the next experiments to visualize the data and get histograms, normality plots, box plots, and more probability ranges.

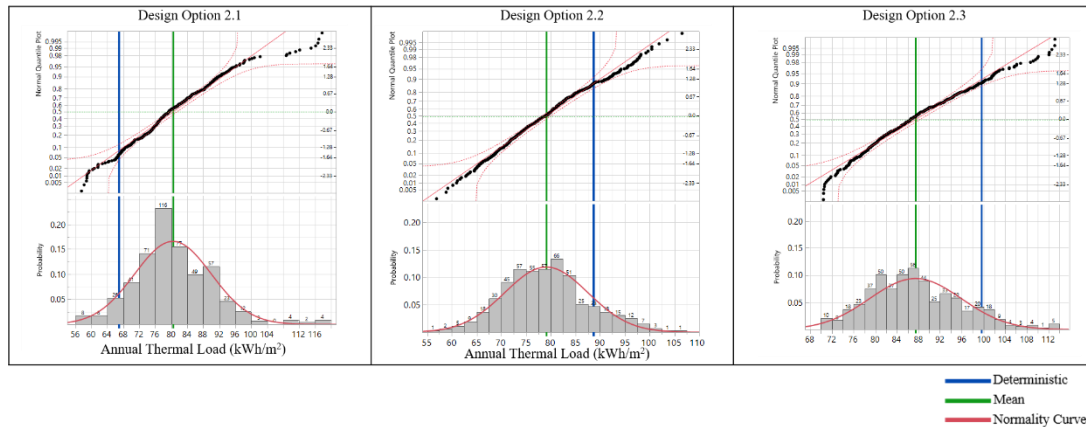
## **6.2 Test Case 2 (TC2-CA) Results and Discussion**

In this test case, the advanced framework is applied to compare the performance of three design options described in Chapter 5. The predicted annual thermal load for each design option is simulated and compared using two metrics of KPI and KRI. In the deterministic method, only the mean values for input parameters are used to run energy simulations and a single output is obtained for each design option. On the other hand, in the probabilistic method a pool of 500 samples from a normal distribution is created for each design option. The samples are inserted into the building energy simulation process. In total, 1500 simulations are run to get the probability distribution of the simulation outputs for the three design options.

The KPI for each design option is predicted using the deterministic method. The KRIs are obtained from the probabilistic simulation outputs for each design option. Software JMP [8] is used to visualize the data, calculate KRIs, and analyze the probability



distributions. Figure 6-2 illustrates the deterministic and probabilistic results of annual thermal loads ( $\text{kWh/m}^2$ ) for the three design options using histograms (bottom) and normal quantile plots (top).



**Figure 6-2 Simulation results in terms of building annual thermal load by three design options of test case 2.**

The color coding of histograms shown in Figure 6-2 is similar to Figure 6-1. In each top graph shown in Figure 6-2, the black points representing the data points are distributed around a diagonal red line. The more the datapoints are falling along the diagonal line, the closer is the distribution to the normal distribution. The horizontal green dashed lines depict the median point in the data set for each design option and the red dashed lines show the confidence limits. The confidence interval is set to 0.95 for all the data sets. The histograms (bottom graphs) show the relative frequency of the results. The vertical green lines show the mean values, and the vertical blue lines represent the deterministic results associated with each design option.

Looking at the plots, there is a clear indication of lack of fit to normal distribution in most design options. Especially, the main difference from normality is evident in the tails rather than in the middle. Furthermore, the normality of the distributions is assessed using the Shapiro Wilk W test (goodness of fit test). In this test, the null hypothesis is that the data are from a normal distribution. Small p-values reject the null hypothesis, meaning there is enough evidence that the data are drawn from a non-normal population [8]. The test results are listed in Table 6-2.

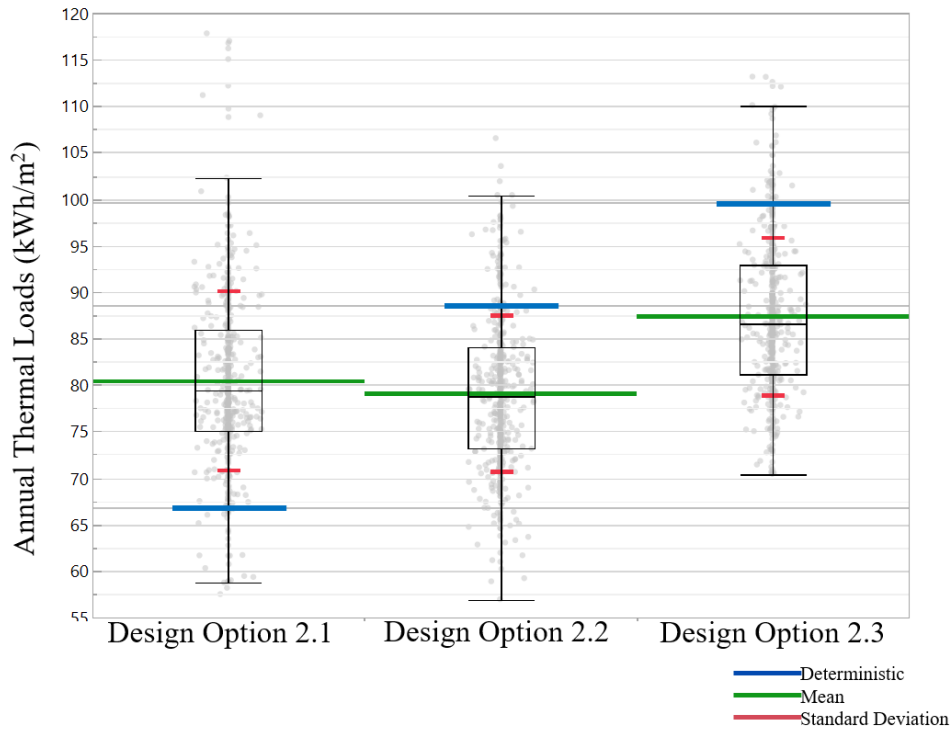
**Table 6-2 Shapiro Wilk W test results for test case 2.**

	<b>Design Option 2.1</b>	<b>Design Option 2.2</b>	<b>Design Option 2.3</b>
<b>W</b>	0.968047	0.990805	0.981366
<b>Prob&lt;W</b>	<.0001	0.0033	<.0001

Note: H0 = The data is from the normal distribution. Small p-values reject H0.

The results show that the p-values are less than the predefined significance level (0.05), in all three design options. Thus, we can reject the null hypothesis and conclude that the data are not from populations with normal distributions.

Figure 6-3 shows the boxplots to further discuss the probability distributions of the results for each design option. The data points, quantiles, mean values, standard deviations, and the deterministic result for each design option are superimposed on the quintile box plot.



**Figure 6-3 Box Plot of building annual thermal load vs. design type for test case 2.**

The gray points illustrate the data points and the boxplots (shown in black lines) depict the quantiles, dividing the range of the data into four continuous intervals with equal probabilities (25%). The red lines on each boxplot show the standard deviation of the results. The green lines show the mean value for each design option, compared to the blue lines that show the deterministic results. 25% of the data are less than the value of the first quartile. The median value for each design option separates the data into two halves. 75% of the set are less than the value of the third quartile for each design option. The summary of the results for each design option is described as follows:

1) Design Option 2.1 shows a range of expected annual thermal load from 57.50 kWh/m<sup>2</sup> to 117.85 kWh/m<sup>2</sup> with a mean value of 80.44 kWh/m<sup>2</sup>, a standard deviation of 9.63 kWh/m<sup>2</sup>, and a variance of 92.74 (kWh/m<sup>2</sup>)<sup>2</sup>. The deterministic result shown by the predicted KPI is equal to 66.83 kWh/m<sup>2</sup>, which is less than the first quantile (located in the first 25% of the data).

2) Design Option 2.2 shows a range of thermal load from 56.93 kWh/m<sup>2</sup> to 106.56 kWh/m<sup>2</sup> with a mean value of 79.11 kWh/m<sup>2</sup>, a standard deviation of 8.43 kWh/m<sup>2</sup>, and a variance of 71.06 (kWh/m<sup>2</sup>)<sup>2</sup>. The deterministic result shown by the predicted KPI is equal to 88.59 kWh/m<sup>2</sup>, which is higher than the third quantile (located in the fourth 25% of the data).

3) Design Option 2.3 shows a range of thermal load from 70.44 kWh/m<sup>2</sup> to 113.18 kWh/m<sup>2</sup>, with a mean value of 87.44 kWh/m<sup>2</sup>, a standard deviation of 8.49 kWh/m<sup>2</sup>, and a variance of 72.08 (kWh/m<sup>2</sup>)<sup>2</sup>. The deterministic result shown by the predicted KPI shows the value of 99.65 kWh/m<sup>2</sup>, which is higher than the third quantile (located in the fourth 25% of the data).

Based on the deterministic results, it could be concluded that Design Option 2.1 would have the best energy performance, followed by options 2.2, and 2.3. However, based on the results obtained from the probabilistic method, Design Option 2.2 shows the lowest KRIs. Design Option 2.1 has the second lowest mean, but the highest standard deviation and variance. Design Option 2.3 has the highest mean value but the second ranked standard deviation and variance.

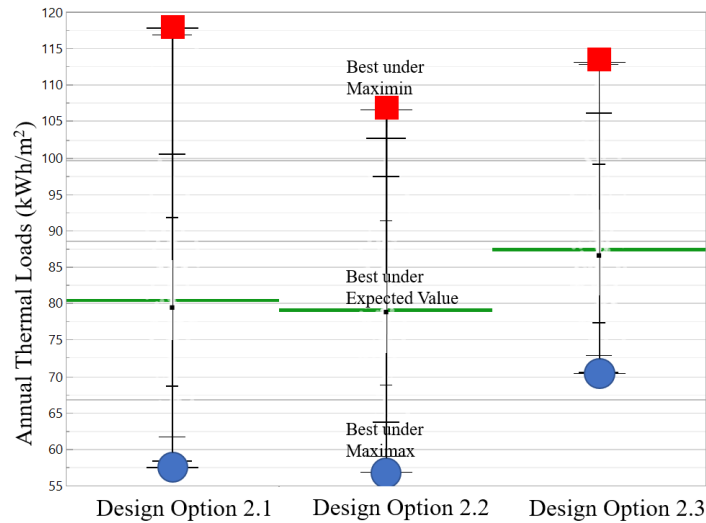
The deterministic results do not match with the probabilistic results in terms of performance ranking order. The optimal solutions for deterministic and probabilistic methods, options 2.1 and 2.2, respectively, are different. The major research finding here is that including the uncertainties of inputs in the simulations can lead to probability distributions of the output and change the performance ranking of the design options, which can significantly influence the design decision making. Based on the expected value decision making criterion, Design Option 2.2 has the best performance, Design Option 2.1 stands as the next option, and Design Option 2.3 shows the worst predicted thermal energy performance. The maximax and maximin decision-making criteria are discussed using the data shown in Table 6-3.

**Table 6-3 Building thermal load under specific probability for test case 2.**

		Probabilities of Annual Thermal Load (kWh/m <sup>2</sup> )							
		0.0%	10.0%	25.0%	50.0%	75.0%	90.0%	97.5%	100.0%
<b>Design</b>	<b>2.1</b>	57.50	68.65	74.97	79.38	85.93	91.78	100.51	117.85
<b>Options</b>	<b>2.2</b>	56.93	68.91	73.18	78.87	84.10	91.37	97.50	106.57
	<b>2.3</b>	70.44	77.39	81.04	86.57	92.96	99.10	106.11	113.19

Building annual thermal load is identified under 8 probabilities in Table 6-3. The probabilities from 0.0% to 100.0% refer to the chance of occurrence ranging from 0 to the value of (x). Using this data, the building thermal load at any probability could be identified. Figure 6-4 compares the best design options under different decision-making

criteria for test case 2.



**Figure 6-4 Design decision making suggestions under expected value, maximax, and maximin criteria for test case 2.**

According to the results the minimum and maximum thermal loads are at a lower level with Design Option 2.2 ( $56.93 \text{ kWh/m}^2$  and  $106.57 \text{ kWh/m}^2$ , respectively) compared to the other two design options. Therefore, Design Option 2.2 is confirmed to have the best performance, based on expected value, maximax, and maximin criteria.

The effect of deterministic and probabilistic results on the ranking of the design options based on different decision-making criteria are summarized as follows:

1. Deterministic: Design Option 2.1 has the best performance, followed by Design Options 2.2, and 3.
2. Probabilistic:

2.1 Expected value criterion: Design Option 2.2 has the best performance, followed by Design Options 2.1, and 2.3.

2.2 Maximax criterion: Design Option 2.2 has the best performance, followed by Design Options 2.1, and 2.3.

2.3 Maximin criterion: Design Option 2.2 has the best performance, followed by Design Options 2.3, and 2.1.

The results show that the best design option suggested by the deterministic method (Design Option 2.1) is different from the best design option suggested by the probabilistic method (Design Option 2.2). All three decision-making criteria using the probabilistic method suggest the same best design option (Design Option 2.2), although there are discrepancies in the second-best design options. The second-best design option suggested by the expected value and the maximax criteria is Design Option 2.1, while the second-best design option suggested by the maximin criterion is Design Option 2.3.

### **6.3 Test Case 3 (TC3-IL) Results and Discussion**

A hypothetical design decision-making problem is presented in this test case to demonstrate the application of the advanced framework in a new design set, different from test case 2 because of the use of a new probability distribution, other than the normal distribution, for some parameters. The building thermal load is measured using deterministic and probabilistic methods and the results are compared in terms of their impacts in the process of design decision making. This decision-making problem consists of two phases. In the first phase, three different design options are compared in terms of

building annual thermal load. Then the best design option is selected (based on the expected value criterion) and compared against a new design option to find the best available design option. The second phase of the design generation and evaluation is performed to represent the iterative and continuous nature of building design in practice and create different scenarios to demonstrate the applications of probabilistic methods versus deterministic method.

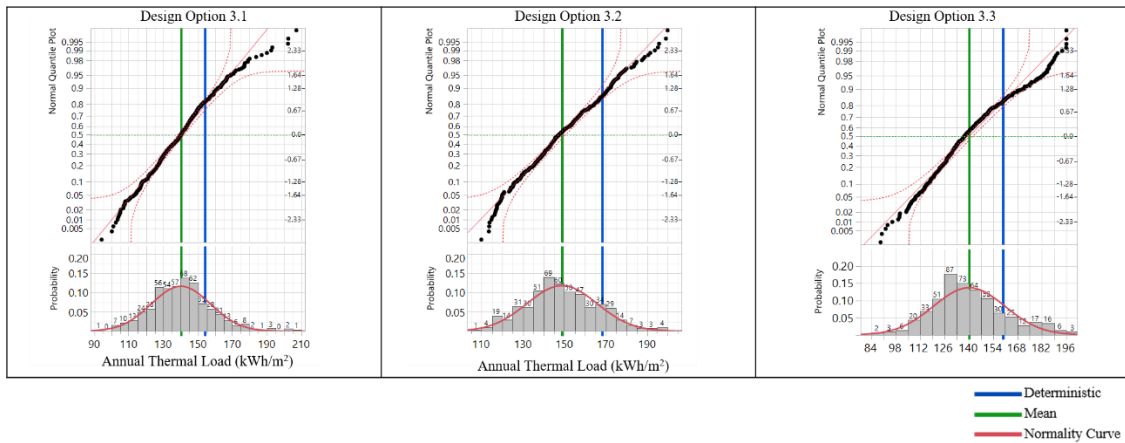
The deterministic method is applied in both phases and the results are compared with the outcome of the probabilistic method. In the probabilistic method, 500 samples are generated for each design option. Some design inputs are sampled from the normal distribution, while others are sampled from the Poisson distribution. More detailed description of the experiment is presented in the previous chapter (Chapter 5). In total, 1500 simulations are run in the first phase and 500 more simulations are performed in the second phase of this design decision making experiment.

Similar to test case 2 (TC2-TX), software JMP [8] is used to visualize the data, analyze the probability distributions, and get the KRIs.

### **6.3.1 TC3\_IL, phase 1**

Figure 6-5 illustrates the deterministic and probabilistic results of annual thermal loads (kWh/m<sup>2</sup>) for the three design options studied in phase 1.





**Figure 6-5 Simulation results in terms of building annual thermal load by three design options of phase 1\_test case 3.**

Figure 6-5 shows the distribution of results with histograms (bottom), and the normality plots (top). In each top graph shown in Figure 6-5, the black points representing the data points are distributed around a diagonal red line. The more the datapoints are falling along the diagonal line, the closer is the distribution to the normal distribution. The horizontal green dashed lines depict the median point in the data set for each design option and the red dashed lines show the confidence limits. The confidence interval is set to 0.95 for all the data sets. The histograms (bottom graphs) show the relative frequency of the results. The vertical green lines show the mean values, and the vertical blue lines represent the deterministic results associated with each design option.

Looking at the plots, there is a clear indication of lack of fit to normal distribution in all three design options. Especially, the main difference from normality is evident in the tails rather than in the middle. Furthermore, the normality of the

distributions is assessed using the Shapiro Wilk W test (goodness of fit test). In this test, the null hypothesis (H0) is that the data are forming a normal distribution. A small p-value rejects the null hypothesis, meaning there is enough evidence that the data are drawn from a non-normal population. The test results are listed in Table 6-4.

**Table 6-4 Shapiro Wilk W test results.**

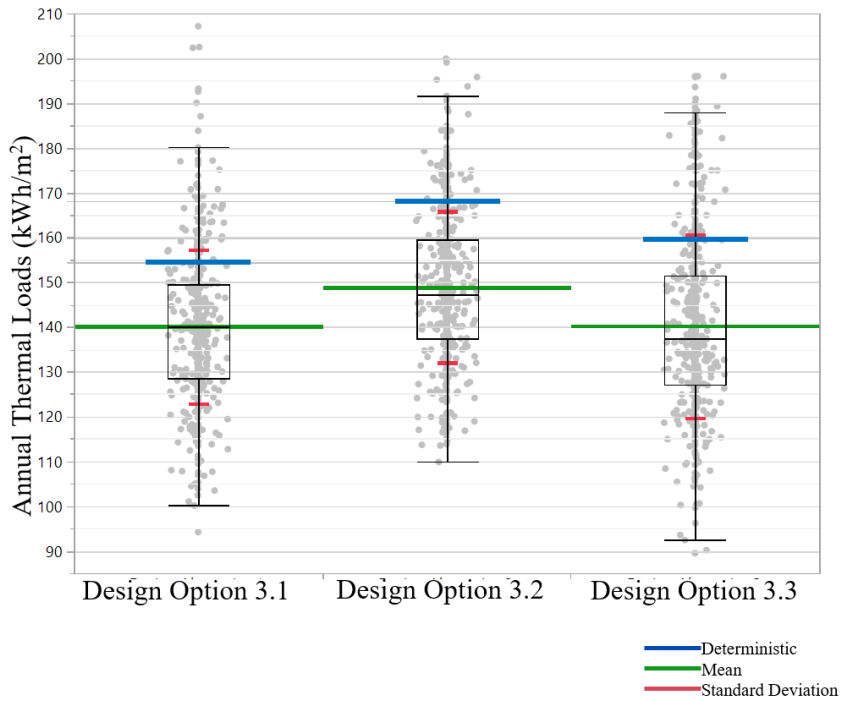
	<b>Design Option 3.1</b>	<b>Design Option 3.2</b>	<b>Design Option 3.3</b>
<b>W</b>	0.985816	0.991713	0.976497
<b>Prob&lt;W</b>	<.0001	0.0069	<.0001

Note: H0 = The data is from the normal distribution. Small p-values reject H0.

The null hypothesis for this test is that the data are normally distributed. The Prob < W value listed in the output is the p-value. If the chosen alpha level is 0.05 and the p-value is less than 0.05, then the null hypothesis that the data are normally distributed is rejected. If the p-value is greater than 0.05, then the null hypothesis is not rejected [8]. The results show that the p-values in the three design options are less than the predefined significance level (0.05). Thus, we can reject the null hypothesis and conclude that the data are not from populations with normal distributions in those design options. The reason could be drawing some input variables from Poisson distribution, also the nonlinear nature of equations in the building energy simulations.

Figure 6-6 shows the boxplots to further discuss the probability distributions of the results for each design option. The data points, quantiles, mean values, standard

deviations, and deterministic result for each design option are superimposed on the quintile box plot.



**Figure 6-6 Box Plot of building annual thermal load vs. design type for test case 3, phase 1.**

The gray points illustrate the data points and the boxplots (shown in black lines) depict the quantiles, dividing the range of the data into four continuous intervals with equal probabilities (25%). The red lines on each boxplot show the standard deviation of the results. The green lines show the mean value for each design option, compared to the blue lines that show the deterministic results. The summary of the results for each design option is described as follows:

1) Design Option 3.1 shows a range of expected annual thermal load from 94.19 kWh/m<sup>2</sup> to 207.17 kWh/m<sup>2</sup> with a mean value of 140.16 kWh/m<sup>2</sup>, a standard deviation of 17.19 kWh/m<sup>2</sup>, and a variance of 295.50 (kWh/m<sup>2</sup>)<sup>2</sup>. The deterministic result shown by the KPI value predicts the building annual thermal load to be equal to 154.42 kWh/m<sup>2</sup>, that is in the last quartile (located in the fourth 25% of the data).

2) Design Option 3.2 shows a range of thermal load from 109.85 kWh/m<sup>2</sup> to 199.93 kWh/m<sup>2</sup> with a mean value of 148.88 kWh/m<sup>2</sup>, a standard deviation of 16.96 kWh/m<sup>2</sup>, and a variance of 287.64 (kWh/m<sup>2</sup>)<sup>2</sup>. The deterministic result shown by the KPI value is equal to 168.19 kWh/m<sup>2</sup>, that is higher than the third quartile (located in the fourth 25% of the data).

3) Design Option 3.3 shows a range of thermal load from 89.48 kWh/m<sup>2</sup> to 196 kWh/m<sup>2</sup>, with a mean value of 140.29 kWh/m<sup>2</sup>, a standard deviation of 20.52 kWh/m<sup>2</sup>, and a variance of 421.07 (kWh/m<sup>2</sup>)<sup>2</sup>. The deterministic result indicated by the KPI value shows the value of 159.71 kWh/m<sup>2</sup>, that is higher than the third quartile (located in the fourth 25% of the data).

Based on the deterministic results, it can be concluded that Design Option 3.1 shows the best energy performance, followed by options 3.3, and 3.2. However, the probabilistic results provide a more comprehensive outcome with KRIs. Design Option 3.1 has the lowest mean value of thermal load, closely followed by options 3.3, and 3.2. The mean values of design options 3.1 and 3.3 are competing too closely to distinguish the best option but referring to standard deviation and variance shows that Design Option

3.1 has considerably lower values of standard deviation and variance. This information helps identifying Design Option 3.1 as the best building performance.

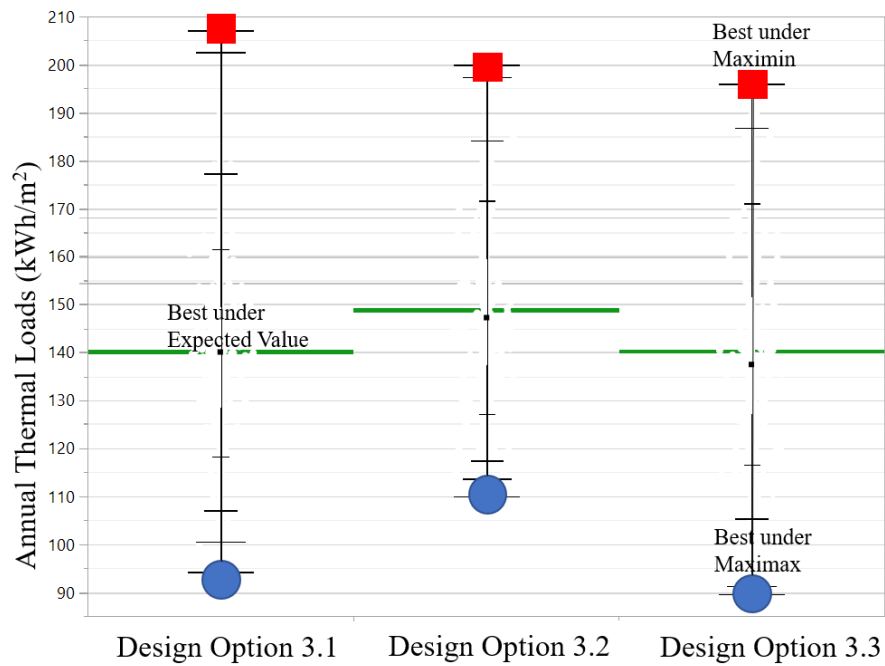
In this test case the deterministic results match with the probabilistic results measured by mean values in terms of performance ranking order. The major finding here is that including the uncertainties of inputs in the simulations can lead to probability distributions of the output but will not necessarily change the performance ranking of design options, at all instances. The ranking order of design options is the same between deterministic and probability methods (using mean values) in test case 3. Based on the expected value decision making criterion, Design Option 3.1 has the best performance, Design Option 3.3 stands as the next option, and Design Option 3.2 shows the worst predicted thermal energy performance. This test case shows a different example compared to the previous test case (TC2-TX) in terms of ranking orders using deterministic and probabilistic methods (using expected value, maximax, and maximin criteria). This is understandable because the two cases have different probability distributions of input parameters. Yet this demonstrates a need for further investigation to find out under what conditions we will need to utilize or not utilize probabilistic methods (Phase 2 of this test case showed just another design option can lead to different ranking results.)

In addition, the maximax and maximin decision-making criteria are discussed using the data shown in Table 6-5.

**Table 6-5 Building thermal load under specific probability for test case 3, phase 1.**

		Probabilities of Annual Thermal Load (kWh/m <sup>2</sup> )							
		0.0%	10.0%	25.0%	50.0%	75.0%	90.0%	97.5%	100.0%
<b>Design</b>	<b>3.1</b>	94.19	118.18	128.64	139.95	149.61	161.60	177.29	207.17
<b>Options</b>	<b>3.2</b>	109.85	127.14	137.45	147.18	159.64	171.45	184.26	199.93
	<b>3.3</b>	89.48	116.59	127.07	137.41	151.46	170.89	186.91	196.00

Building annual thermal load is identified under 8 probabilities in Table 6-5. The probabilities from 0.0% to 100.0% refer to the chance of occurrence ranging from 0 to the value of (x). Using this data, the building thermal load at any probability could be identified. Figure 6-7 compares the best design options under different decision-making criteria for test case 3, phase 1.



**Figure 6-7 Design decision making suggestions under expected value, maximax, and maximin criteria for test case 3, phase 1.**

According to Table 6-5, the minimum and maximum thermal loads are lower in the case of Design Option 3.3 (89.48 kWh/m<sup>2</sup> and 196.00 kWh/m<sup>2</sup>, respectively) compared to the other two design options. Therefore, Design Option 3.3 shows the best performance, based on the maximax and maximin criteria, although the expected value criterion suggested Design Option 3.1 to be the best option.

The effect of deterministic and probabilistic results on the ranking of the design options based on different decision-making criteria are summarized as follows:

1. Deterministic: Design Option 3.1 has the best performance, followed by Design Options 3.3, and 3.2.
2. Probabilistic:
  - 2.1 Expected value criterion: Design Option 3.1 has the best performance, followed by Design Options 3.3, and 3.2.
  - 2.2 Maximax criterion: Design Option 3.3 has the best performance, followed by Design Options 3.1, and 3.2.
  - 2.3 Maximin criterion: Design Option 3.3 has the best performance, followed by Design Options 3.2, and 3.1.

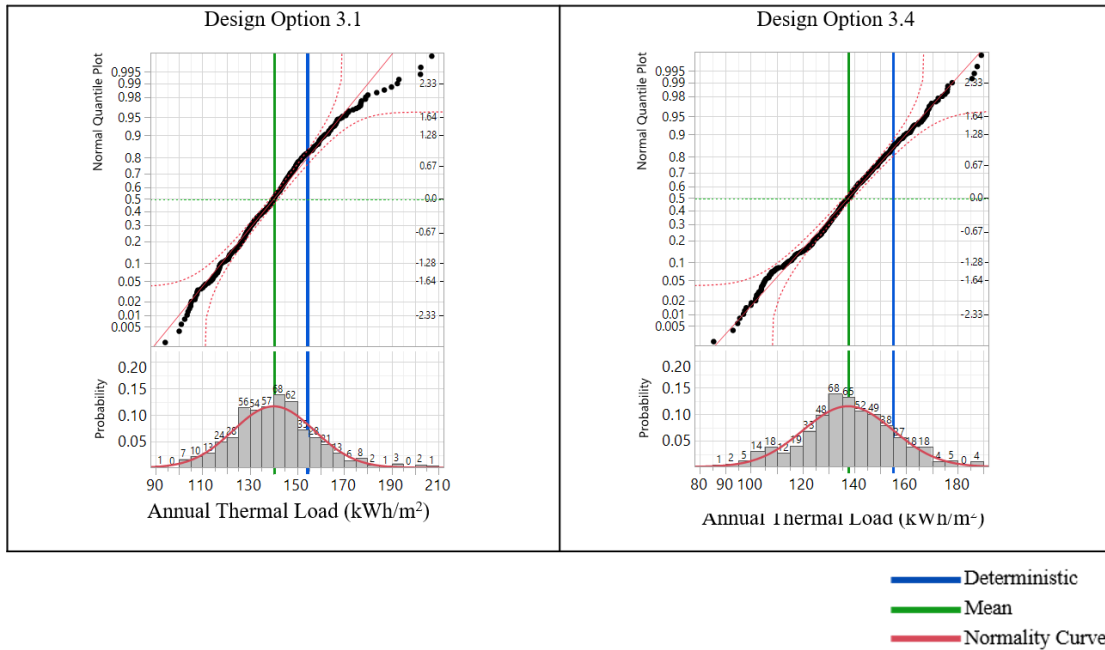
The results show that the best design option suggested by the deterministic method (Design Option 3.1) is the same as the best design option suggested by the expected value

criterion, but different from the best design option suggested by the maximax and maximin criteria (Design Option 3.3). Furthermore, the deterministic and the expected value criterion follow the same ranking orders for the second and third best design options (Design Option 3.3, followed by Design Option 3.2). However, the second-best design option suggested by the maximax and maximin criteria are different. The maximax criterion shows Design Option 3.1 as the second-best option, while the second-best design option suggested by the maximin criterion is Design Option 3.2.

### **6.3.2 TC3\_IL, phase 2**

In this phase, the best design option from phase 1 (based on the expected value criterion) is compared to a new design option (named as Design Option 3.4) to make the final design decision. Design Option 3.4 is just another design option and the modeling, sampling, simulation, and post processing workflow are similar to the other three design options. Some of the design input variables including exterior wall and floor R-values, WWR, glazing U-value and SHGC (details are presented in the previous chapter) are slightly improved in this design option to compare the results with the best design option from phase 1. Figure 6-8 illustrates the deterministic and probabilistic results of annual thermal loads ( $\text{kWh/m}^2$ ) for the two design options.





**Figure 6-8 Simulation results in terms of building annual thermal load by three design options for test case 3, phase 2.**

The legends in Figure 6-8 are similar to those in Figure 6-5. Looking at the plots in Figure 6-8, there seems to be a good fit to normality in Design Option 3.4. But there is a clear indication of lack of fit to normal distribution in Design Option 3.1, especially, the main difference from normality is evident in the tails rather than in the middle. Furthermore, the normality of the distributions is assessed using the Shapiro Wilk W test (goodness of fit test). In this test, the null hypothesis ( $H_0$ ) is that the data are forming a normal distribution. A small p-value rejects the null hypothesis, meaning there is enough evidence that the data are drawn from a non-normal population. The test results are listed in Table 6-6.

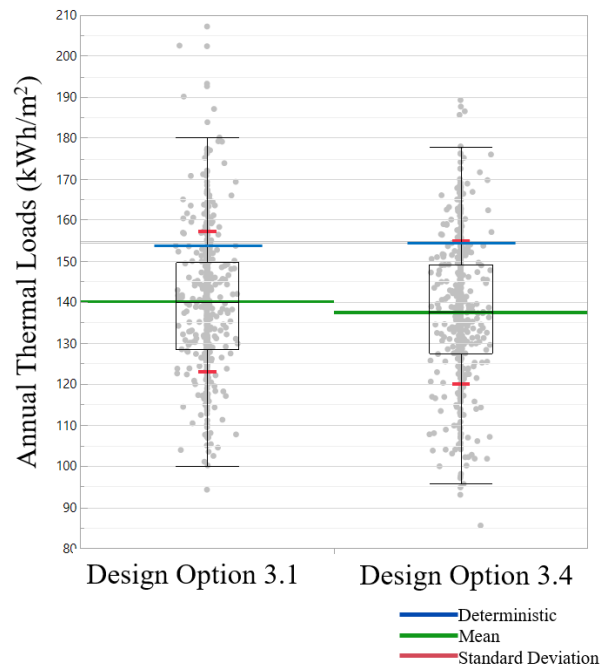
**Table 6-6 Shapiro Wilk W test results.**

	<b>Design Option 3.1</b>	<b>Design Option 3.4</b>
<b>W</b>	0.985816	0.995059
<b>Prob&lt;W</b>	<.0001	0.1110

Note: H0 = The data is from the normal distribution. Small p-values reject H0.

The null hypothesis for this test is that the data are normally distributed. The Prob < W value listed in the output is the p-value. If the chosen alpha level is 0.05 and the p-value is less than 0.05, then the null hypothesis that the data are normally distributed is rejected. If the p-value is greater than 0.05, then the null hypothesis is not rejected [8]. The results show that the p-values in the first design option is less than the predefined significance level (0.05). Thus, we can reject the null hypothesis and conclude that the data are not from populations with normal distributions in those design options. The reason could be drawing some input variables from Poisson distribution, also the nonlinear nature of equations in the building energy simulations. On the other hand, in Design Option 3.4 we cannot reject the null hypothesis, since the p-value is larger than 0.05.

Figure 6-9 shows the boxplots to further discuss the probability distributions of the results for each design option. The data points, quantiles, mean values, standard deviations, and deterministic result for each design option are superimposed on the quintile box plot.



**Figure 6-9 Box Plot of building annual thermal load vs. design type for test case 3, phase 2.**

The gray points in Figure 6-9 illustrate the data points and the boxplots (shown in black lines) depict the quantiles, dividing the range of the data into four continuous intervals with equal probabilities (25%). The red lines on each boxplot show the standard deviation of the results. The green lines show the mean value for each design option, compared to the blue lines that show the deterministic results. The summary of the results for each design option is described as follows:

1) Design Option 3.1 shows a range of expected annual thermal load from 94.19 kWh/m<sup>2</sup> to 207.17 kWh/m<sup>2</sup> with a mean of 140.16 kWh/m<sup>2</sup>, a standard deviation of 17.19 kWh/m<sup>2</sup>, and a variance of 295.50 (kWh/m<sup>2</sup>)<sup>2</sup>. The deterministic result shown by the KPI

value predicts the building annual thermal load to be equal to 154.42 kWh/m<sup>2</sup>, which is higher than the third quantile (located in the fourth 25% of the data).

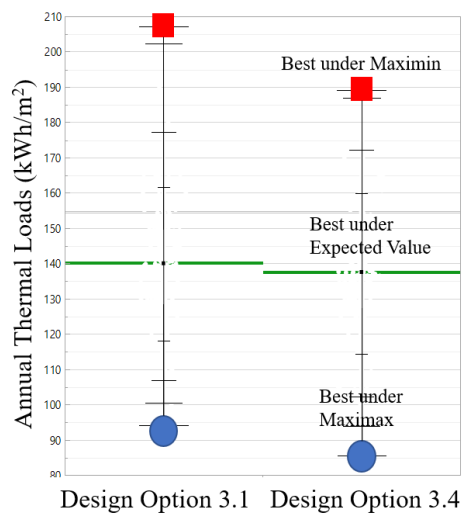
2) Design Option 3.4 shows a range of thermal load from 85.45 kWh/m<sup>2</sup> to 189.22 kWh/m<sup>2</sup> with a mean value of 137.58 kWh/m<sup>2</sup>, a standard deviation of 17.4 kWh/m<sup>2</sup>, and a variance of 302.76 (kWh/m<sup>2</sup>)<sup>2</sup>. The deterministic result shown by the KPI value is equal to 154.76 kWh/m<sup>2</sup>, which is higher than the third quantile (located in the fourth 25% of the data).

Based on the deterministic results, it can be concluded that Design Option 3.1 has a slightly better energy performance, compared to Design Option 3.4. However, the probabilistic results show that Design Option 3.4 has lower KRIs than Design Option 3.1. In this phase of test case 3, the deterministic results do not match with the probabilistic results in terms of design ranking order. Moreover, there is less than 25% chance of occurrence for predicted KPIs to happen considering the uncertainties (Figure 6-9). Based on the expected value decision making criterion, Design Option 3.4 has a better performance than Design Option 3.1. The maximax and maximin decision-making criteria are discussed using the data shown in Table 6-7.

**Table 6-7 Building thermal load under specific probability for test case 3, phase 2.**

		Probabilities of Annual Thermal Load (kWh/m <sup>2</sup> )							
		0.0%	10.0%	25.0%	50.0%	75.0%	90.0%	97.5%	100.0%
Design Options	3.1	94.19	118.18	128.64	139.95	149.61	161.60	177.29	207.17
	3.4	85.46	114.27	127.46	137.47	149.05	159.89	172.03	189.22

Building annual thermal load is identified under 8 probabilities in Table 6-7. The probabilities from 0.0% to 100.0% refer to the chance of occurrence ranging from 0 to the value of (x). Using this data, the building thermal load at any probability could be identified. Figure 6-10 compares the best design options under different decision-making criteria for test case 3, phase 2.



**Figure 6-10 Design decision making suggestions under expected value, maximax, and maximin criteria for test case 3, phase 2.**

According to Table 6-7, the minimum and maximum thermal loads are lower in the case of Design Option 3.4 (85.46 kWh/m<sup>2</sup> and 189.22 kWh/m<sup>2</sup>, respectively) compared to the other design option. Therefore, Design Option 3.4 shows the best performance, based on expected value, maximax, and maximin criteria.

The effect of deterministic and probabilistic results on the ranking of the design options based on different decision-making criteria are summarized as follows:

1. Deterministic: Design Option 3.1 has better performance than Design Option 3.4.

2. Probabilistic:

2.1 Expected value criterion: Design Option 3.4 has the better performance, followed by Design Option 3.1.

2.2 Maximax criterion: Design Option 3.4 has the better performance, followed by Design Option 3.1.

2.3 Maximin criterion: Design Option 3.4 has the better performance, followed by Design Option 3.1.

The results show that the better design option suggested by the deterministic method (Design Option 3.1) is different from the better design option suggested by expected value, maximax, and maximin criteria (Design Option 3.4).

## **6.4 Summary**

The proposed probabilistic framework (the initial and the advanced) coupled with the BIM and parametric tools takes the mean and standard deviation values of a set of input variables, described earlier (Chapter 5) to generate input samples. A set of samples is generated for each input parameter to run the simulations repeatedly and deliver a range of simulation output.

The major finding of this research is that compared with the existing deterministic method for architectural design ranking, using probabilistic methods can result in

significantly different design decision to be made, or different design options to be selected, using expected value, maximax, and maximin decision making criteria.

However, this is not always the case that probabilistic methods lead to different ranking orders than deterministic methods, as test case 1 demonstrated.

Applying probabilistic methods provides the opportunity to use different decision-making criteria including expected value, maximax, and maximin to deal with different risk attitudes. The probabilistic results are analyzed based on different decision-making criteria for each test case. In test case 1, all of these decision-making criteria lead to selecting the same design option, which is matching the deterministic results, as well.

Besides the best design option, the ranking of all the design options is matching among deterministic and the other three decision making criteria. However, the rankings of design options could be different between any two of deterministic, and probabilistic expected value, maximax, and maximin. In test case 2 the best design option suggested by the three decision making criteria is the same, but different from the deterministic result. Also, the rankings of design options in test case 2 are different between expected value and maximax versus maximin criteria. Test case 3-phase 1 shows a discrepancy between the best design option suggested by deterministic and expected value methods versus maximax and maximin criteria. The ranking order of design options are different between maximax and maximin criteria. Test case 3 phase 2 demonstrates a case where the ranking order of deterministic method is different from expected value, maximax, and maximin. Table 6-8 shows the matching status between the ranking order of every pair of the two measures in the test cases.

**Table 6-8 The summary of ranking orders and matching status between different design decision making criteria.**

<b>Design Options/ranking order</b>	<b>Test case 1</b>	<b>Test case 2</b>	<b>Test case 3, phase 1</b>	<b>Test case 3, phase 2</b>
<b>Deterministic vs. expected value</b>	Matching (1.3, 1.1, 1.2)	Different (2.1, 2.2, 2.3 vs. 2.2, 2.1, 2.3)	Matching (3.1, 3.3, 3.2)	Different (3.1, 3.4 vs. 3.4, 3.1)
<b>Deterministic vs. maximax</b>	Matching (1.3, 1.1, 1.2)	Different (2.1, 2.2, 2.3 vs. 2.2, 2.1, 2.3)	Different (3.1, 3.3, 3.2 vs. 3.3, 3.1, 3.2)	Different (3.1, 3.4 vs. 3.4, 3.1)
<b>Deterministic vs. maximin</b>	Matching (1.3, 1.1, 1.2)	Different (2.1, 2.2, 2.3 vs. 2.2, 2.3, 2.1)	Different (3.1, 3.3, 3.2 vs. 3.3, 3.2, 3.1)	Different (3.1, 3.4 vs. 3.4, 3.1)
<b>Expected value vs. maximax</b>	Matching (1.3, 1.1, 1.2)	Matching (2.2, 2.1, 2.3)	Different (3.1, 3.3, 3.2 vs. 3.3, 3.1, 3.2)	Matching (3.4, 3.1)
<b>Expected value vs. maximin</b>	Matching (1.3, 1.1, 1.2)	Different (2.2, 2.1, 2.3 vs. 2.2, 2.3, 2.1)	Different (3.1, 3.3, 3.2 vs. 3.3, 3.2, 3.1)	Matching (3.4, 3.1)
<b>Maximax vs. maximin</b>	Matching (1.3, 1.1, 1.2)	Different (2.2, 2.1, 2.3 vs. 2.2, 2.3, 2.1)	Different (3.3, 3.1, 3.2 vs. 3.3, 3.2, 3.1)	Matching (3.4, 3.1)

In addition to different ranking orders in different methods, an interesting observation about the probability distribution of the energy simulation outputs was made. The results of the Shapiro-Wilk W tests for test cases 2 and 3 showed that the null hypothesis, which was based on the normality of the output distribution, may be rejected even when the probability distributions of all the input variables were normal (test case 2). This might happen due to nonlinearity of the equations in the building energy simulations.



This research has studied the probabilistic approaches versus conventional deterministic method of design decision making and concludes that the investigation of probabilistic methods in architectural design forms a major future research area in computational design.

## CHAPTER 7

### CONCLUSION

This research has proposed, prototyped, and tested a new framework to implement probabilistic methods in the field of performance-based building design decision-making, using parametric methods and Building Information Modeling (BIM). The probabilistic methods including uncertainty analysis and risk assessment are investigated to provide a more robust basis for building performance prediction and design decision-making. This research integrates Monte Carlo uncertainty analysis into parametric modeling and simulation to provide a probabilistic framework for building thermal energy prediction and design decision-making based on different attitudes towards risk. The research objectives, questions, and significance are discussed in Chapter 1. The relevant literature review and research gaps are presented in Chapter 2.

This research intends to improve the reliability of building design process by considering the uncertainties and probabilities in the building performance analysis. This work studies building thermal energy loads as an important aspect of the building performance. Building performance simulation tools, integrated with uncertainty analysis, provide the probability distribution of simulation output. The proposed analysis begins with obtaining the mean and standard deviation values of design input parameters from the existing literature. The parametric tools are used to generate a set of samples for each input parameter with normal or Poisson distribution (the differences and applications of these probability distributions are discussed in the previous chapters). The simulation model runs iteratively using the sample values and the results are presented using the

statistical measures. The deterministic results are compared with probabilistic results and different decision-making criteria (expected value, maximax, and maximin), which are introduced to represent different risk scenarios in building design decision-making. More detailed description of the method and the proposed framework are presented in Chapters 3 and 4.

This work has presented three test cases to demonstrate the proposed framework. As the first test case, a hypothetical residential unit in College Station, TX, USA, was designed. The input variables were sampled from normal probability distributions. The probabilistic results agreed with the deterministic results in this test case. As the second test case, a modular classroom building in Los Angeles, CA, USA was considered. All the input variables were sampled from normal probability distributions. There were differences between deterministic results and probabilistic results. Also, there were discrepancies among the performance ranking orders suggested by some of the decision-making criteria. The third test case was a hypothetical office building in Chicago, IL, USA. This test case contained two phases, and some of the input variables were sampled from normal probability distributions, while others were sampled using Poisson distributions. Some differences between the results from deterministic and probabilistic methods were observed in this test case. Also, the performance ranking orders were different using some of the decision-making criteria. Further details about the test cases and the results are discussed in Chapters 5 and 6.

This section discusses the contributions of this research to the body of knowledge. Some limitations inherent in the tools and platforms were experienced during the implementation process, which are discussed in this section. Throughout the process of developing this framework, the potential areas for further research were identified and are discussed in this section.

### **7.1 Contributions to the body of knowledge**

This research proposes a probabilistic framework for energy analysis and building design decision-making. This work has contributed to the body of knowledge in the following ways:

- A novel integrated framework is created for integrating BIM into probabilistic building energy simulation to enhance user interface and system interface for such simulation. This step includes:
  1. Creating a BIM plugin to add probability distributions of design input parameters in BIM.
  2. Developing a data inventory including the probability distributions of thermal properties of building materials, based on the findings from the existing literature.
  3. Creating a parametric platform to run probabilistic energy simulations.
  4. Creating a post-processing platform to compare deterministic results with probabilistic results, and applying different decision-making

criteria to enable designers to consider different attitudes towards risk in design decision-making.

- Different performance rankings of design options are found in test cases 2 and 3 when comparing deterministic and probabilistic methods. In addition, different test cases led to different conclusions about such rankings, which demonstrates the significant impact of probabilistic methods on design decision-making.

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### **7.1.1 BIM Add-in**

The development of Building Information Modelling (BIM) tools allows modeling complicated building designs and transferring data from design tools to analysis tools. Adding probability distributions of design input parameters using BIM API is proposed. Four new parameters are added to the building materials in Revit, including the standard deviation of thickness, standard deviation of thermal conductivity, standard deviation of density, and standard deviation of specific heat capacity. The mean values of these parameters utilize the existing Revit parameter values.

### **7.1.2 Data Inventory**

The probability distributions of the thermal properties of some building materials are collected from the existing literature and listed in a Microsoft Excel spreadsheet to be read by the Revit addin. The probabilistic data are added to the Building Information Models (BIMs) as parameters with appropriate probability distributions and stored in a

new Microsoft Excel spreadsheet to be used in the future samplings and probabilistic energy simulations.

### **7.1.3 Probabilistic Energy Simulations**

The capabilities of parametric tools are deployed to integrate probabilistic methods with building energy performance assessment.

### **7.1.4 Post Processing and Risk Analysis for Design Decision-Making**

The simulation results are recorded and stored to produce the histograms and charts for data visualization and further analysis. The simulation results from the deterministic method are compared with the findings of probabilistic method, in terms of design ranking orders. Three different decision-making criteria are discussed to allow designers to consider their risk preferences.

## **7.2 Limitations**

The limitations of the research include the following. This research used only three simple test cases of building thermal energy simulations to demonstrate and validate the proposed framework, with only 200 (Test case 1) and 500 (test cases 2 and 3) samples derived from normal or Poisson probability distributions. Other building performance criteria or other probability distribution types are not applied in this research. The probability distributions of the uncertain input variables are obtained from the literature not actual material experiments. For some input variables, the author had to make assumptions about the standard deviation values due to the lack of information. Only the

random and Latin Hypercube Sampling (LHS) methods are used for sampling in this research. Other sampling methods are not applied in this research.

Another limitation of this research is that only Revit is used as a BIM tool, and only the thermal properties of materials are selected to add the probability distributions. Other information such as material quantity or cost are beyond the scope of this research.

### **7.3 Future Research**

This research adopts probabilistic methods in performance-based building design decision making targeting building energy performance and using BIM and parametric tools. This work is just a small piece of a larger puzzle with the aim of improving building performance. An application of the proposed framework for the other aspects of building design and performance analysis, including daylight, thermal comfort, construction cost, and building life cycle cost analysis could be the potential areas for further research.

Further development of the proposed framework may focus on using the probability distributions of design input variables to search for the optimal solution using different optimization algorithms. Choosing the input values for an optimization process out of an appropriate probability distribution allows searching for the optimal solutions considering their probability of occurrence. This method may improve the reliability of optimization results since the probability of occurrence of each design option is considered.

More complex design case studies may be performed to investigate the capabilities of BIM tools and parametric design in adopting the probabilistic methods in building design decision-making. As an example, this framework may be implemented in multi-

objective design optimization problems such as an aviation facility planning. It may support the architects to design more efficient ticketing halls based on the probability distribution of different passenger flow situations. The uncertainty of the number of passengers in the ticketing halls in different times may be analyzed to allow the architects to test different design scenarios. Multiple objectives such as minimizing travel distance, maximizing the usable area, minimizing construction and operational cost among other objectives can be taken into consideration. This framework can also be applied in adaptive facade design process. The uncertainties of external environment such as weather data or internal environment such as occupants' behavior, make the adaptive facade design challenging. Further research in adopting this framework for uncertainty analysis and risk assessment in adaptive facade design may be valuable.

The conditional probability and Bayesian network are also promising fields of research related to probabilistic optimization. The conditional probability allows quantifying the probability of an event, assuming that another event has already occurred in the past. The Bayesian inference updates the prior belief, which is a starting point for the optimization, to a posterior outcome based on additional data and information. This method may facilitate the integration of expert knowledge with design optimization and may improve the simulation-based optimization and calibration in architectural design decision-making. For instance, Heo et al. (2012) applied a Bayesian approach to update the probability distributions of the uncertain parameters in building energy retrofit simulations using the observed information and already known specifications of the



building. The uncertainties in their research included indoor temperature during heating, infiltration rate, and discharge coefficient.

The dependency of the input variables and the application of joint probability is another potential area for further research. Whether or not the input variables with different probability distributions are dependent to each other would affect the size of design space and the notion of joint distribution may be useful in this field.

Furthermore, for the future research, it is recommended to work on the maximax and maximin criteria based on, for example, first and 99<sup>th</sup> percentiles instead of the most extreme values in the output range. In this way, inference can be applied to find statistically significant differences between design options.

Other sampling and uncertainty analysis methods and probability distribution types for building energy analysis are encouraged for further research. Other probability distributions including the uniform distribution and the rectangular distribution may be used in probabilistic simulation with undecided design variables and strategies, such as the number of stories or the building height [3], [102], which is not in the scope of this research. Using emulator models, such as Gaussian Process (GP) models, seems promising in the field of probabilistic design optimization. In this method, a simpler substitution of the original complicated model is created, and the uncertainties associated with the emulator are quantified. This method could handle the time and cost extensive simulations that are needed in the process of probabilistic design optimization.

## **7.4 Summary**

This chapter has presented the conclusions and contributions of this research, discussed the limitations, and proposed areas for further research.

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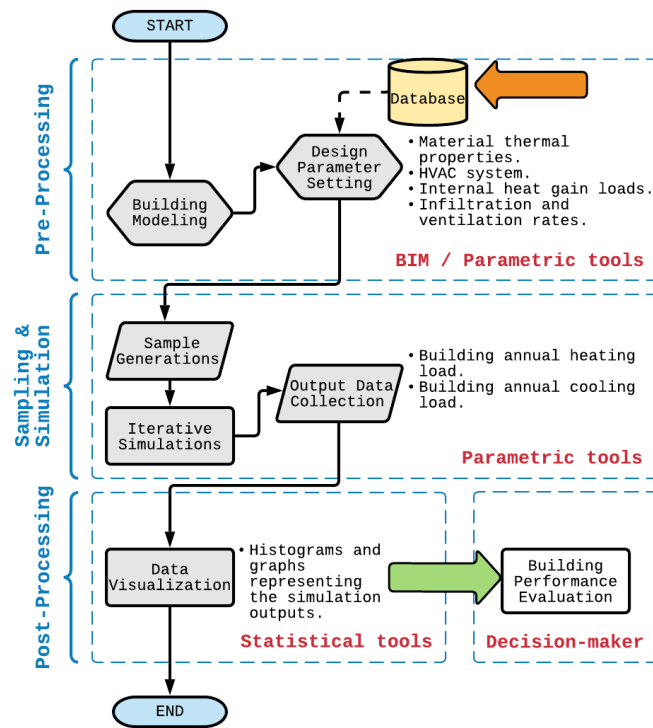
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## APPENDIX

This study presents a new framework to implement probabilistic methods in the field of performance-driven building design decision-making, using Building Information Modeling (BIM) and parametric tools. Figure 11 presents the workflow including the key steps of this process, data being transferred, variables, and the software:



**Figure 11** BIMProbE workflow for probabilistic performance-based design decision-making.

This framework considers the uncertainties in building energy simulations including material properties, internal heat gains, and infiltration and ventilation rates (more details about this framework are presented in [27]). This framework targets the Revit-based building design process and has three main steps described below:

## **Pre-processing**

The building geometry is modeled in a BIM authoring tool such as Revit. An external application named BIMProbE is developed to set the probability distributions for thermal properties of building materials based on the real-world material properties learned from literature studies and retrieved from an external database (Microsoft Excel). The mapping between the BIM model and the Excel-based database is performed through BIM API and using object-oriented programming.

Building elements consist of exterior walls, interior walls, roofs, floors, and windows.

This program will find and collect opaque components including walls, roofs, and floors.

The material IDs associated with each material is identified to collect the thermal

properties. The thermal properties of building materials including thickness, thermal

conductivity, and R-value can be collected from the BIM model. For instance, the

thickness can be accessed as the width of each layer of the building components. As an

example, a Structurally Insulated Panel (SIP) wall type consists of six layers of

Plasterboard, Wood, Timber Insulated Panel – OSB, Timber Insulated Panel –

Insulation, Timber Insulated Panel – OSB, and Sand/Cement Screed. The width of each

layer of an SIP wall can be identified as the thickness of that specific material. If the

thermal properties of a material are missing in the Revit model, the program will create a

thermal asset for that material and will set the thermal properties according to the

corresponding values in the Excel database.

BIMProbE add-in will automatically create the required shared parameters to add the

probability distributions to the building material thermal properties and bind them to

each building material in the project. This application searches for the material names in the Excel database to assign the correct value to each parameter. This process begins with an attempt to open the external Excel database. Once the user starts this addin, a window will pop up asking the user to select an external Excel file. If the user selects an Excel file, the program will automatically start reading it cell by cell. The program will check the sanity of the data first and if there is no error found, it will continue with the rest of this process. The probability distributions (including the mean and standard deviation) for each material type are set according to the corresponding values in the Excel database. At the end of this process, BIMProbE allows writing the mean and standard deviation values of the thermal properties to a new Excel spreadsheet to be used for later steps of sampling and simulation.

Other design input parameters required for building energy simulations including Heating, Ventilation, and Air Conditioning (HVAC) system specifications, internal heat gain loads, infiltration and ventilation rates, and operational schedules are added using parametric tools such as Grasshopper, which is the visual programming environment for Rhinoceros.

### **Sampling and simulation**

The information prepared in the pre-processing step is used for sample generation and iterative simulations. Using Latin Hypercube Sampling method, N samples for each design input variable are generated and N energy simulations are run for each design option (building forms) in Grasshopper. The simulation outputs (building annual heating

and cooling loads) are recorded in Grasshopper and written to Excel using TT Toolbox plugin for Grasshopper [28]. For each round of the energy simulation, a corresponding value from the sample pool of each design variable ( $x_{\text{uncer}_i}$ ) is selected and inserted into the simulation model, and as a result,  $N$  output values are obtained. The set of outputs whose elements correspond to the samples are  $Y = \{y_1, y_2, y_3, \dots, y_m\}$ ,  $m = N$ , where  $Y$  denotes the space of output values, which are the results of building thermal load simulations.

In the deterministic approach, all the design variables, regardless of being deterministic or uncertain, are assigned to their associated mean ( $\mu_i$ ) as a fixed value ( $x_i = \mu_i$ ). Fixing all the input variables at their mean values, the energy simulation is run once and a single output  $y_{\text{det}} = f(\mu_1, \mu_2, \mu_3, \dots, \mu_n)$  is obtained, where ( $\mu_1, \mu_2, \mu_3, \dots, \mu_n$ ) are the means of the design variables.

### **Post-processing and design decision-making**

The post-processing phase consists of data analysis and graphical presentation of the simulation results. This phase is conducted using a statistical software known as JMP. The data are collected in Grasshopper and exported to Excel for post-processing. The JMP [29] add-in for Excel provides interactive graphics and tables that enable the user to identify relationships visually and examine patterns. The histogram demonstrations, normality plots and box plots are used for risk assessment and data visualization. The output results are represented by the values of deterministic and probabilistic outputs using two metrics of KPI and KRIs. In addition, design options are ranked

according to the criteria of expected value, maximax, and maximin. The information provided in this process could help design decision-makers with building performance evaluation including uncertainties and comparing the probabilistic results with the deterministic results.

All the scripts are available in the link below:

<https://github.com/Aban6?tab=projects>