Influence of Uncertainty in User Behaviors on the Simulation-Based Building Energy Optimization Process and Robust Decision-Making

by

Nu Ri Bae

A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
(Architecture)
in the University of Michigan
2016

Doctoral Committee:

Assistant Professor Lars Junghans, Chair
Associate Professor Aline J. Cotel
Professor Peter D. von Bülow
Professor Jean D. Wineman

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

ABSTRACT

Computer-based simulations have been widely used to predict building performances. Building energy simulation tools are generally used to perform parametric studies. However, the building is a complex system with a great number of variables. This leads to a very high computational cost. Therefore, using a building optimization algorithm coupled with an energy simulation tool is a more promising solution. In this study, EnergyPlus is connected to a genetic algorithm that uses a probabilistic search technique based on evolutionary principles.

Various sources of uncertainty exist in simulation-based building optimization problems. This study aims to investigate the influence of occupant behavior-related input variables on the optimization process. To integrate the uncertainty into the optimization process, a stochastic approach using the Latin hypercube sampling (LHS) method is employed. The varying input variables are defined by the LHS method, and each sampling run generates 14 samples. Five optimization parameters are used, and the recommendations for parameter settings of each parameter are generated as the optimization result.

It is important to provide a decision maker with a decision-making framework to support robust decision-making from the generated recommendations. A clear or relatively clear tendency of recommendations toward

a particular parameter setting is observed for three parameters. For these three parameters, the frequency of recommendation is identified to be a good indicator for the robustness of the most recommended setting. The test of proportion is performed to investigate the statistical significance between parameter settings. For the other two parameters, recommendations are comparatively evenly distributed among parameter settings, and the statistical significance is not shown. In this case, the Hurwicz decision rule is utilized to select an optimal solution.

This dissertation contributes to the field of building optimization as it proposes a method to integrate uncertainty in input variables and shows the method generates reliable results. Computational time is reduced by using the LHS method compared to the case of using a random sampling method. While this study does not include all potential input variables with uncertainties, it provides significant insight into the role of input variables with uncertainty in the building optimization process.

CHAPTER 1

INTRODUCTION

The building sector has been a major contributor to energy consumption and greenhouse gas (GHG) emissions. Thus, the building sector becomes the focal point of mitigating GHG emissions, especially in developing and developed countries. Computational building energy analysis tools integrated into the building design process can help decision-making for energy-efficient building planning. However, the existence of uncertainties is a common problem of computer simulation tools. The uncertainty needs to be addressed and investigated in order to ensure reliability and robustness of the result.

1.1 Global Climate Change

Climate change due to GHG emissions is one of the most urgent global issues that humankind is confronting. It is projected that global surface temperature over the 21st century will continuously increase (Figure 1.1). Further global warming will be likely to continue even under the scenario of a substantial decrease in GHG emission. Continuous global warming will not only increase the surface temperature but also modify the entire climate system; sea levels are anticipated to rise, the ocean is projected to be warmer and acidified, the global glacier volume will keep decreasing, more frequent and intense extreme precipitation events are expected, and more frequent and longer heat waves with more frequent hot extremes will be very likely. The changes in global climate consequently involve negative impacts and risks for natural and human systems [1]. Thus, it is critical to immediately reduce energy consumption from fossil fuels and strive for sustainable development in order to decrease the speed of global warming due to GHG emissions.

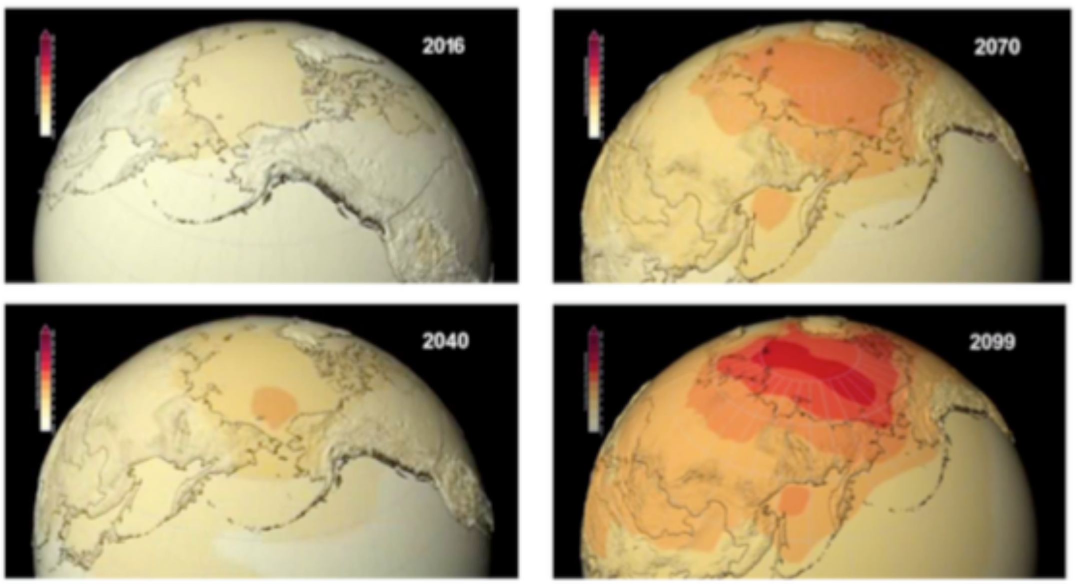

Figure 1.1 Global surface temperature projection over the 21st century[1] (Source: NASA's Scientific Visualization Studio)

[1] This is a projection under the scenario RCP 4.5 by IPCC (Intergovernmental Panel on Climate Change). RCP 4.5 is one of the two intermediate scenarios of future GHG emissions, which assumes approximately 650 ppm CO2-equivalent in 2100 [1,160].

1.2 Building Energy Use

The building sector has great potential to mitigate climate change, because it currently makes a huge contribution to the worldwide energy consumption and GHG emissions. The building sector consists of residential (e.g. single- and multi-family residences) and commercial buildings (e.g. offices, stores, restaurants, warehouses, government buildings) [2], and it is responsible for 40% of the total global energy consumption and 30% of annual GHG emissions. Also, the building sector is projected to have a continuous growth of energy demand and resultant GHG emissions. This is because of the combinational effect of lower energy efficiency in existing building stock and new construction [3,4]. The total building stock is anticipated to keep growing in number because the rate of constructing new buildings is faster than demolishing existing buildings [5]. Therefore, the energy consumption and GHG emissions of the building sector should be constrained, and it will greatly contribute to the mitigation of global climate change.

The large amount of energy consumption and GHG emissions in the building sector is more prevalent in developed and developing countries. In the United States (U.S.), the building sector is responsible for 41.1% (22.5% in the residential sector and 18.6% in the commercial sector) of the total U.S. primary energy consumption (Figure 1.2) [2,3]. The building sector is the biggest energy consumer among all sectors in the U.S. as it consumes 44% more than the transportation sector and 36% more than the industrial sector. It is notable that the U.S. building sector alone used 7% of the total global primary energy in the year of 2010.

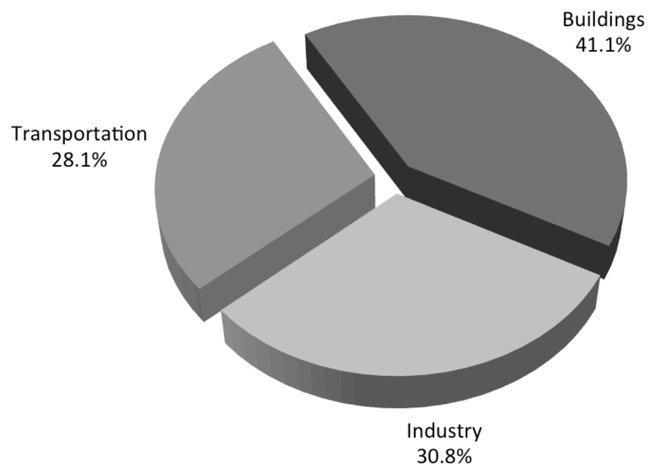

Figure 1.2 U.S. primary energy consumption by sector

The U.S. building sector mainly depends on fossil fuels that generate GHG emissions. 75% of energy consumption in the building sector comes from fossil fuel resources including coal (36%), natural gas (34%), and petroleum (5%). Furthermore, the U.S. building sector accounts for 73.6% of the U.S. total electricity consumption, while the U.S. electricity generation largely depends on coal-based power plants. 48.3% of the total U.S. electricity generation is fueled by coal, and coal has higher carbon intensity among fossil fuels [2]. This indicates that the building sector has been a great contributor to GHG emissions in the U.S., and as a consequence, the U.S. building sector is responsible for 44.6% of the total U.S. carbon dioxide (CO_2) emissions (Figure 1.3) [6].

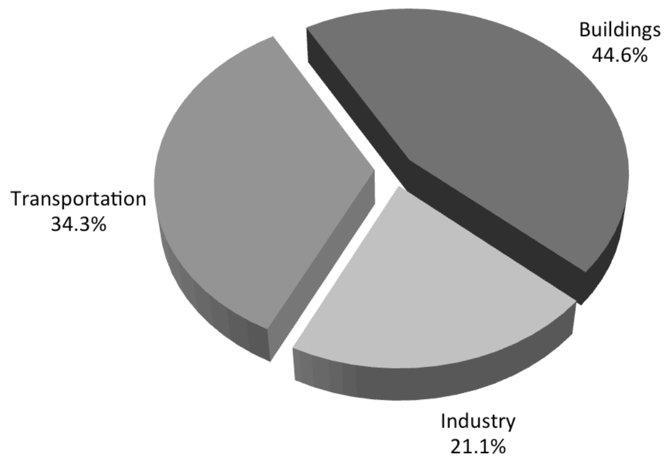

Figure 1.3 U.S. CO_2 emissions by sector

In short, the building sector has been responsible for a substantial share of energy consumption and global warming. It uses more energy than any other single sector in the U.S. However, this implies a lot of potential for mitigation of GHG emissions in the building sector. A significant reduction in the building sector is therefore expected to be the key to decreasing energy consumption and GHG emissions at the national level. Buildings should be designed, built, and operated at the very least in more energy efficient ways and eventually should become carbon-neutral [6].

Achieving carbon-neutral in the building sector should start with decreasing energy demand by improving energy efficiency in both new and existing building stock. Then, on-site energy generation needs to be considered. Thanks to technological developments, more and more products of higher energy efficiency, such as building materials, mechanical systems, and electrical appliances, are available on the market. The efficiency of renewable energy systems such as solar collectors, solar cells, and wind turbines has also been improving. However, these technologies are generally more expensive than conventional products, which holds back building owners from selecting such high energy efficient products for their projects.

1.3 Computational Analysis Tools

Computational analysis tools for building energy performance such as thermal simulation tools and computer-based building optimization can be useful to overcome the gap between the higher energy efficiency and the increased investment cost. Computational analysis provides an objective assessment of whether the increased cost of an investment balances the benefits of energy savings [7,8]. For example, building simulation or optimization results may show that a more expensive energy-efficient window system will lead to cost-savings due to reduced heating and cooling energy demands. Wind turbines and building-integrated photovoltaics (BIPV) that require high initial investment costs may result in making profits from selling the excess electricity back to the grid.

A common problem of computer-based simulation/optimization tools is the existence of uncertainties. For computational analysis tools, uncertainties exist in almost every part including the calculation process, simulation model design, material properties, cost data, weather data, and boundary conditions [8–11].

This study is motivated by the uncertainties in computer-based building optimization. A method to integrate uncertainty in input variables into the optimization process is developed, and the robustness of the consequent results is evaluated. Finally, a strategy to select a solution from the generated optimization results is introduced.

1.4 Organization of This Dissertation

This dissertation is organized as follows:

Chapter 1 provides the general background of this research by presenting the global issues and the challenges for the building sector.

Chapter 2 summarizes the academic background of this study by introducing building energy simulation and optimization.

Chapter 3 provides the background knowledge of various decision theories.

Chapter 4 presents research questions, objectives, and the scope of this study.

Chapter 5 describes the research method, and displays the step-by-step procedure of this study.

Chapter 6 demonstrates the optimization results and introduces a robust selection technique from available alternatives in the results.

Chapter 7 concludes the key findings, discusses the contributions of this study, and suggests directions for future research.

CHAPTER 2

BUILDING ENERGY SIMULATION AND OPTIMIZATION

Buildings have a relatively long lifespan compared to manufactured goods, and thus how they are designed and built have a long-term impact on the building's energy consumption as well as occupant comfort. Also, it is difficult and costly to alter the building once it is constructed. Therefore, design decisions that affect the entire life cycle of a building should be made very carefully on the basis of accurate evaluation from the early design stage. Computational analysis such as building simulation and optimization can be a useful tool to evaluate and compare different alternatives for a building project. This chapter explains building optimization coupled with a simulation program.

2.1 Building Energy Performance Simulation

Building energy performance simulation tools have been widely used to analyze energy performance and thermal comfort of buildings. A variety of building energy simulation tools is available on the market. The "Building Energy Software Tools Directory (BEST-D)" has a list of 122 tools and provides information about each tool's capabilities [12]. Building energy simulation programs are developed based on similar modeling principles. They typically consist of an internal engine that performs thermal simulations using mathematical and thermodynamic algorithms, and a graphical user interface that helps users to manage input and output as well as to understand the functionality of the engine. For example, DOE-2 and EnergyPlus are the two most popular simulation engines distributed by Lawrence Berkeley National Laboratory (LBNL), and eQUEST and DesignBuilder are the graphical user interfaces for the engines of DOE-2 and EnergyPlus, respectively. However, thermodynamic models, graphical user interfaces, purpose of use, life-cycle applicability, and data exchange ability with other software applications are different between programs. Figures 2.1 and 2.2 demonstrate the types of input, data flow, and typical structure of simulation tools [13].

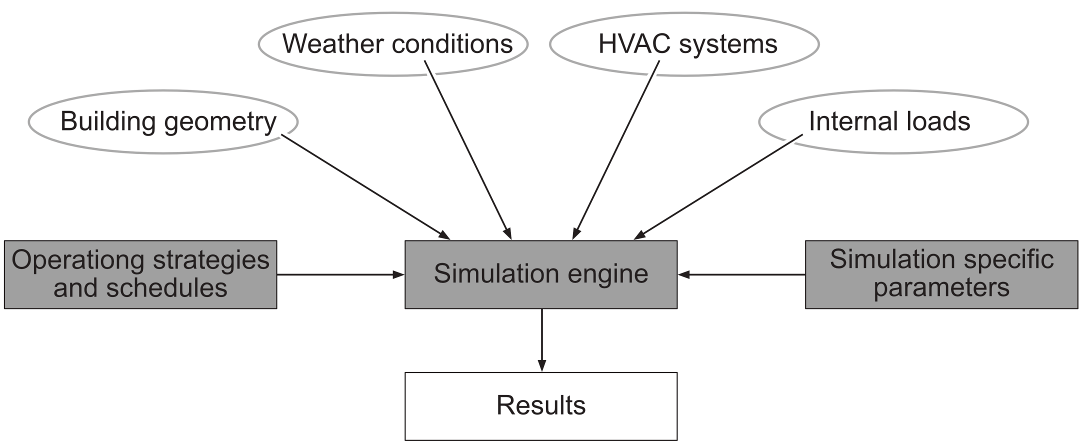

Figure 2.1 General data flow of simulation engines

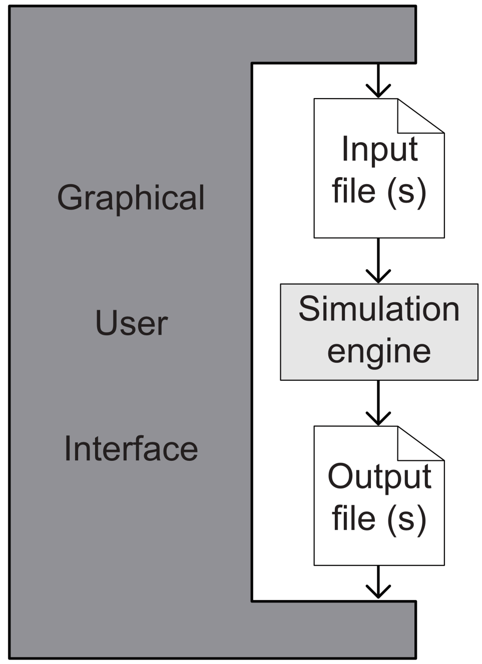

Figure 2.2 General structure of simulation tools

A brief history of computer-based simulation programs for building energy performance is introduced by Hong et al. [14]. Research on building simulations emerged in the 1960s, and early studies in the 1960s and 1970s are mostly about fundamental theory and algorithms of load calculation. From the start of the use of building simulation, it was already considered important for energy-efficient building design. In the late 1970s and early 1980s, due to rapidly diffused desk-top personal computing, building simulation received attention. This is the time when popular building energy simulation programs such as DOE-2, ESP, and TRNSYS were developed. However, these tools were mainly used in research projects and hardly utilized in practice due to their difficulty and cost. As more and more emphasis was put on global issues such as climate change and environmental protection since the 1990s, creating a healthy and comfortable built environment while reducing energy consumption and environmental impact gained more importance. Hence, building energy simulation tools have become a necessary application, and resultantly started to be used more widely in building design practice.

Maile et al. divide software tools used in the building industry into two types: *design* tools and *simulation* tools. The former is mainly used for sizing HVAC systems based on static calculations. Normally, summer and winter design days, which represent the worst case scenario of weather conditions, are used for sizing HVAC systems to prevent them from failing to meet the required level of thermal comfort. Simulation tools estimate annual energy demand of the building based on dynamic calculations using thermodynamic equations. They are also used to compare different design alternatives as they can calculate resulting energy demand according to each design option. Dynamic simulation programs use a set of climate data and produce time-correlated predictions. Because of the different characteristics, design tools are mainly used in the design stage while simulation tools can be used in all phases of the building's life-cycle. Simulation tools usually generate annual energy performance data, which are also useful for commissioning and operation [13]. The following is a list of the most common topics to which building simulation tools - including design tools and simulation tools - are applicable [14]:

- Building heating and cooling load calculation
- Energy performance analysis for design and retrofit
- Building energy management and control system design
- Compliance with building regulations, codes, and standards
- Cost analysis
- Passive energy saving options
- Computational Fluid Dynamics (CFD)

Building energy simulation tools are generally used to perform parametric studies. The building is a complex system with a great number of variables. This can generate an enormous number of possible combinations of parameter settings, which are usually impractical to deal with due to the high computational cost [15]. On the other hand, parametric studies that deal with parameters one at a time, by changing one parameter while leaving others constant, potentially ignore significant interactive effects between parameters. Therefore, using a building optimization algorithm coupled with an energy simulation tool is a more promising solution [7,15]. In this study, EnergyPlus is connected to an optimization algorithm as a building energy simulation engine to evaluate thermal performance of parameter combinations that are generated by the optimization algorithm.

2.2 Building Energy Optimization

A building is a complicated system that is comprised of a great number of structural, electrical, mechanical, and design elements, and all of these elements need to be chosen from a pool of options. How those elements are chosen and combined defines the characteristics and performance of the building. Because of the great number of building elements and even greater number of their possible combinations, parametric studies using a building energy simulation program is usually inapplicable to find the optimal solution. Instead, building energy optimization would be a successful alternative by generating an optimal solution using various input variables.

2.2.1 Introduction of building energy optimization

The term "building optimization" refers to a method that uses an optimization algorithm to find the optimal combination of parameter settings for building design and renovation. Attia et al. explain automated building performance optimization as "a process that aims at the selection of the optimal solutions from a set of available alternatives for a given design or control problem, according to a set of performance criteria" (p.111) [16]. According to Tian et al., "building energy optimization is a process of identifying the optimal design from a vast number of possible designs that conform to energy performance requirements" (p.2573) [17]. Nguyen et al. distinguish simulation-based optimization from other methods that some researchers use for building optimization, such as an iterative improvement process using computer simulation, sensitivity analysis to optimize building performance without carrying out a mathematical optimization, brute-force search, and expert-based optimization. Simulation-based optimization is described as "an automated process which is entirely based on numerical simulation and mathematical optimization" (p.1044). The authors also mention that "the term 'optimization' (in building performance simulation) does not necessarily mean finding the globally optimal solution(s) to a problem since it may be unfeasible due to the nature of the problem or the simulation program itself" (p.1044) [18]. This is how 'building optimization' is different from optimizations in other sciences that essentially require finding the global optimum.

Building energy optimization in the architectural, engineering, and construction (AEC) industry began to be applied in the late 1980s for building design and operation optimization. By the late 1990s, experienced users who made good use of building energy simulation began to connect their simulation models to optimization. Since 2000, building energy optimization has gained more importance and has been used for multi-objective optimization with the development of mathematical and algorithmic techniques as well as the advanced building simulation tools. Overall, the use of building optimization in the AEC industry was first begun by mechanical and structural engineers and then spread to architects and other engineers [16,18]. As shown in Figure 2.3, the number of published research on optimization in the building science field has been continuously increasing since the early 1990s, but a sharp increase started in 2005. This implies building optimization has been receiving great attention from building science researchers over the last decade [18].

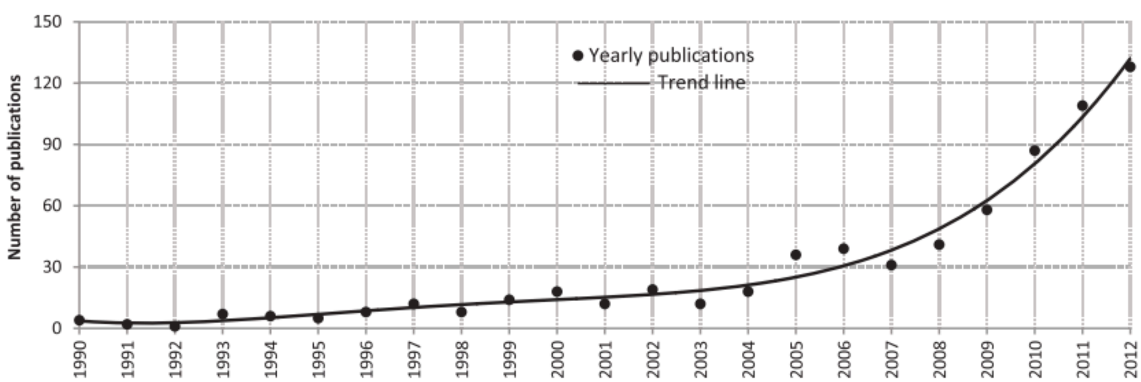

Figure 2.3 The number of publications of building optimization research [18]

Building energy optimization can be effectively used throughout the entire design process to support energy-efficient building design. The most popular use of building optimization is in the early design stage to compare different design alternatives and select an optimal solution. This is especially valuable because early design decisions are normally more influential in defining the final building performance than those made in later stages [17]. Building optimization can also be helpful in the late design stage and even during building operation after construction. An operation strategy of HVAC systems can be selected and fine-tuned by performing optimization in the late design stage. During the building operation stage, the most effective building control can also be determined by optimization [16].

There are two major components of building energy optimization: building energy simulation engine and optimization engine. The energy simulation and optimization are combined and have a cyclic relationship. The optimization engine provides input data for the simulation engine, and then the simulation engine generates the output data (e.g. energy consumption, cost). The optimization engine repeats this process until the optimal solution is obtained. Building energy optimization generates optimal solutions according to a defined target (i.e. objective function). The targets can be construction cost, energy performance, life-cycle cost, greenhouse gas emissions, and thermal comfort.

Despite the potential powerful use of building optimization for finding optimal solutions, optimization is not in wide use in building design practice; this is partly because optimization is not yet widely integrated in building simulation tools. Moreover, the use of optimization involves a high cost. The cost of computational tools not only include the purchase cost; they also involve the use cost including the labor and computer resources. The more complex the optimization and simulation tools, the more money, time, and effort are required. In practice, a major goal of building energy optimization is therefore to define an optimization process that can find the optimal solution in a less computationally intensive way [19].

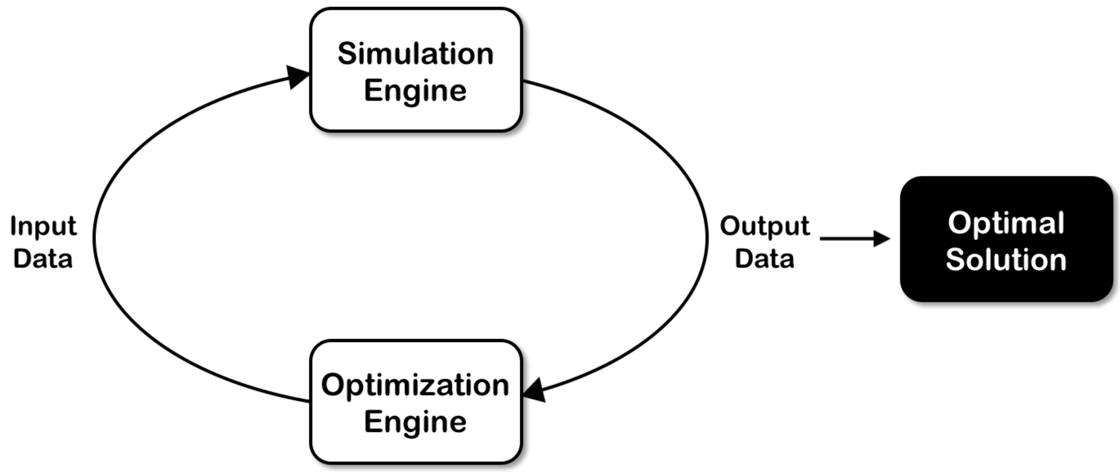

Figure 2.4 The coupling loop of simulation-based optimization

2.2.2 Topics of building optimization

The most commonly studied topics in building optimization are listed as follows [16]:

- Building layout and form [20–23]
- Geometry, position and density of fenestration [24]
- Building envelope and fabric constructions [7,25–31]
- Daylighting performance [32,33] and automated control of solar shadings [34,35]
- Natural ventilation strategies [36,37]
- Shape and functional structure of buildings as well as heat source utilization [38]
- Heating, ventilating, and air-conditioning (HVAC) systems sizing [39,40]
- HVAC system control parameters and/or strategy [41–46]
- Thermal comfort [47,48]

- HVAC system configuration synthesis [49]
- Managing of energy storage [50] and automated model calibration [51]
- Simultaneous optimization of building envelope and HVAC elements [52–55]
- Simultaneous optimization of building construction, HVAC system size, and system supervisory control [47]
- Simultaneous optimization of building construction, HVAC elements and energy supply system [56,57].

In most cases, the objectives are related to energy and/or cost [16]. In other words, input design variables are optimized to be either energy effective or cost effective, or both; this depends on the selection of objective functions. According to the constraints and/or the number of functions to be optimized, building optimization can mainly be categorized into two groups: single-objective and multi-objective. The level of building insulation, for example, can be optimized to minimize either heating and cooling energy demand or investment cost, in the case of using a single-objective function. If a multi-objective function is used, the insulation can also be optimized to reduce energy demand while considering cost effectiveness at the same time.

Previous studies on building optimization are mainly about efficiency of optimization algorithms and search techniques [7,19,54,58,59] as well as to prove optimization is a useful method for the research topics listed above [15]. The major deficiency is that research on uncertainties in building optimization is limited though uncertainties are a common problem for computer-based simulation and optimization. Uncertainty studies have been conducted largely in regard to uncertainty analysis and sensitivity analysis, but little research has dealt with the uncertainty topic in the simulation-based building optimization research community. The uncertainty issue is important for the reliable use of building optimization because it is related to the robustness of the optimal solutions [18].

Some researchers carry out studies on the reliability and robustness of the optimization method to see if it can produce optimal solutions [7,53,58]. It is shown that building optimization is generally reliable and generates optimal solutions that are approximate to the global optimum. For example, Wright and Alajmi find that their optimization results using the genetic algorithm have 2.5% of difference on average from the best solution, which can be considered robust in general in building energy optimization problems [60].

It is also useful to see if simulation-based building optimization is truly effective in improving building performance. With some references to previous studies [53,61–65], it is concluded that building optimization can achieve a 20-30% decrease in building energy consumption in cold and temperate climates compared to the reference building that is not optimized. However, building optimization is not as effective in reducing energy consumption in warmer climates. Cost reduction by using optimization is also marginal and largely influenced by many factors such as the objective function, climate, building model, and optimization algorithm [18].

2.2.3 Optimization algorithms

A great number of optimization algorithms have been developed and applied to the field of automated building energy optimization. Especially since the 2000s, along with advances in algorithmic techniques as well as building energy simulation tools, building optimization has been actively used to handle multi-objective optimization problems in building design. Population-based search algorithms (e.g. evolutionary algorithms, particle swarms) are currently evident in building optimization algorithms, because they are effective to solve single- and multi-objective optimization problems for a large design problem such as architecture [16,18]. The selection of an optimization algorithm is specific to individual research, and thus cannot be generalized. Some examples of considerations for selecting algorithms are: natures of design variables (continuous, discrete, or both); constraints on the objective function; natures of objective functions (e.g. linear or nonlinear); the availability of analytic first and second order derivatives of the objective functions; characteristics of the problem (e.g. static or dynamic); and performance of other similar algorithms [18].

2.2.3.1 Categorization of building energy optimization algorithms

The most commonly used optimization algorithms can be categorized into three groups: (1) enumerative algorithms, (2) deterministic algorithms, and (3) stochastic algorithms. The enumerative algorithms find the best solution by calculating all available options, and therefore are computationally costly.

Deterministic optimization requires that the evaluation function and derivatives should be perfectly known, which is not the case in many practical problems. Also, the evaluation function for the deterministic methods should be continuous, so deterministic optimization does not best suit building design and HVAC system problems due to their nature of discontinuity. Moreover, building optimization is a complex problem that involves many parameters to consider and can be affected by various uncertain sources. In order to cope with this, traditional deterministic studies usually use average values for stochastic parameters, which may lead to a false result having a discrepancy between calculation and the real building. Therefore, stochastic models are more appropriate for building optimization to deal with the uncertainties [66].

Stochastic optimization is also less computationally intensive than the enumerative methods as they use the probabilistic concept using random variables and sampling the search space instead of exploring the entire space. However, this results in the major drawback of stochastic optimization, that is to say, the stochastic algorithms do not guarantee finding the absolute global optimum (See Figure 2.5). They instead produce an acceptable probabilistic estimate of the global optimal solution [16,67,68]. Stochastic methods are generally relatively simple to be employed for complex problems, but are supported by little theoretical foundation for the quality of solutions they generate. This is because they are developed largely depending on customized use in each field through trial and error [67]. Ant colony optimization, particle swarm optimization, sequential search algorithm, and genetic algorithms are examples of stochastic optimization algorithms that have been widely used in the building optimization field.

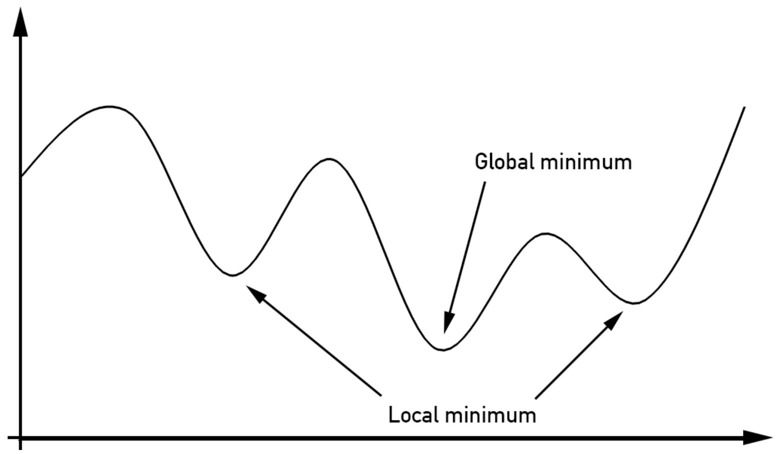

Figure 2.5 Global vs. local optima

Another way to categorize building energy optimization algorithms is to classify them according to the characteristics of parameters: (1) discrete parameter methods and (2) continuous parameter methods. Discrete parameter methods are generally used for building problems because only a finite number of options are available for typical building energy optimization (e.g. wall insulation, glazing insulation, window type, roof type, etc.). Some parameters for which a non-fixed number of options are available, such as window-to-wall ratio, building orientation, and air-tightness, can sometimes be optimized using continuous parameter methods. The simplex method, the pattern search algorithm, the harmony search algorithm, and the multi-directional search algorithm are examples of optimization methods using continuous parameters. Discrete parameter methods include the GA, particle swarm, and sequential search methods [69,70].

2.2.3.2 Particle swarm optimization (PSO)

Particle swarm optimization (PSO) is a stochastic optimization using discrete parameters. The particle swarm based optimizations use probabilistic methods. PSO was initially developed to simulate social behavior representing the movement of individuals of a population (e.g. a bird flock or fish school) toward an optimal position. For example, a swarm of bees has a shared goal to find the best flower in a field. In the PSO algorithm, a swarm represents a population, and each particle stands for possible optimization solution [69–71].

Particles in a swarm share information to find the best possible solution. Each particle (i.e. a potential solution) knows the position of both the best global solution hitherto found by the swarm and the best local solution found by the particle in current population. Going directly to the global best or local best solution does not mean anything because they are already known. Instead, PSO alters particles' speed and make them go towards both the best global and local solutions. The velocity and position of each particle that are updated every iteration are defined by the following equations [69,72]:

$$v^{new} = v^{old} + c_1 r_1 (p^{localbest} - p^{old}) + c_2 r_2 (p^{globalbest} - p^{old})$$

$$p^{new} = p^{old} + v^{new}$$

where

v = particle velocity

p = particle position

r_1, r_2 = independent uniform random values between 0 and 1

c_1 = cognitive acceleration constant

c_2 = social acceleration constant

$p^{localbest}$ = best local solution

$p^{globalbest}$ = best global solution

The numbers for the two acceleration constants are generally given between 0 and 4 [69]. It is said that the best result is obtained when roughly the same numbers are given. When a relatively high number is given to c_1 compared to c_2, each particle wanders too much in the problem space, whereas premature convergence towards a local optimum happens in the contrary situation [72].

One of the advantages of using PSO is that it is the simplest technique among discrete parameter methods. PSO can also solve optimization problems that are partially irregular, noisy, and/or changing over time, which cannot be solved by classic optimization methods. The main disadvantage of the PSO technique is that it does not guarantee the global optimal solution will be found. Additionally, PSO requires a relatively high computational cost compared to GAs, especially when a large number of parameters are considered for optimization. Tuhus-Dubrow and Krarti point out that the GA could yield the optimal solution within the 0.5% of difference from the results by PSO when more than 10 parameters are considered [7,69]. There are some extensions of the PSO algorithm, including inertia function, acceleration constants, natural selection considerations, dynamic adjustment of swarm parameters, and velocity vector constraints. These extensions bring about increased computational intensity, and thus need to be avoided in regard to computational efficiency [71].

2.2.3.3 Sequential search

The common ideas among PSO, sequential search, and GAs are that they use probabilistic methods and repeat a number of iterations to find the global optimum. However, the sequential search technique finds the best solution in each simulation and use it for the next iteration, unlike the GA and PSO methods that use randomly generated parameter settings for each simulation [70]. For example, the Building Energy Optimization (BEopt) tool uses the sequential search technique to find the minimum cost function; starting from the user-defined reference building simulation, the tool simulates each option, and then the option evaluated to be the most effective is selected to be included in the building description for the next iteration. By repeating this process, BEopt outlines a path from the reference building to its optimization target [69].

The following is a generalized summary of the steps of the sequential search techniques [67]:

Step 0. Initialize algorithm parameters and initial point $X_0 \in S$ and set iteration index $k = 0$.

Step 1. Generate a candidate point $V_{k+1} \in S$ according to a specific generator.

Step 2. Update the current point X_{k+1} based on the candidate point and previous points.

Step 3. If a stopping criterion is met, stop. Otherwise update algorithm parameters, increment k and return to Step 1.

Like PSO, the sequential search technique does not assure finding the global optimum, so it is suitable for problems in which finding a reasonable local optimum with limited resources (e.g. time, money, computational cost) is acceptable [68]. There are mainly three kinds of limitations that inhibit finding the correct solution in sequential search techniques due to the interactive effects between different options: invest/divest, large steps, and positive interactions. The invest/divest and large steps cases result from negative interaction among options. In the invest/divest case, the sequential search algorithm eliminates potential optimal options. For example, a high-efficiency HVAC system may have been chosen as the most cost-effective (in regard to increased investment costs and decreased utility costs) option early in the optimization process. It can, however, be evaluated as less cost-effective as a result of improved building envelope performances, hence the optimization algorithm may take this option out from the building design. The large steps case describes a situation that a previously passed, that is not available at the current point, can be more optimal after some iterations. One way to take care of the large steps case is to keep monitoring previous iterations, and if a more cost-optimal point is found, the current point is replaced by it. A final case is due to a positive interaction between two options that create synergy when considered together. For instance, large south-facing windows are more effective for passive solar heating when combined with thermal mass, but the sequential search technique is not always able to find the positive interaction between two options. It can only be found when one option is already chosen [69].

2.2.3.4 Genetic algorithm

Genetic algorithms (GAs) are a population-based algorithm and a type of stochastic algorithm, that uses a probabilistic search technique. GAs are mathematical optimization approaches developed based on the biological evolutionary concept of natural selection. It uses the concept of probability distributions and repeats iterations to find the best solution. The iteration is repeated until the stopping criterion is met, for example, the number of predefined generations is produced or the optimal solution is found [7,70]. Tuhus-Dubrow and Krarti assume that the optimal solution is found if the same solution is generated in twenty consecutive generations [7]. The performance of the GA is related to the size of the search space. If the population is too small, the algorithm is unlikely find the global optimum. On the contrary, if the population is too large, it requires an extended time, therefore becomes inefficient [19,67].

In each generation, a set of possible solutions, called "population," is generated, and the current population is used to produce a new population for the next generation by using crossover, mutation, and reproduction. "Parents" are selected in the current population to produce "children." Then, "children" are evaluated according to the objective function and used to form the new generation. Through selection based on a fitness function, the populations will evolve or converge on fitter solutions. [67,72,73]. One way to do this is "rank weighting"; each solution in the population is tested and ranked in an order of their fitness value, then a virtual roulette wheel is spun to select members to be reproduced for the new population [69]. The concept behind this is that the fitter the solution to the objective function, the more chance it has to be selected by the roulette wheel. In other words, it does not guarantee the fittest member goes through to the next generation, however it provides a very good chance of doing so. In this light, the way that the GA generates new populations can be viewed as a probability distribution.

Once the population for reproduction is formed, solutions are paired for crossover. Crossover creates new solutions (children) by breaking and reassembling paired parents. A pair of parents are broken at a randomly selected crosspoint and then reassembled by swapping the genes after the point, or vice versa. Figure 2.6 illustrates the concept of crossover.

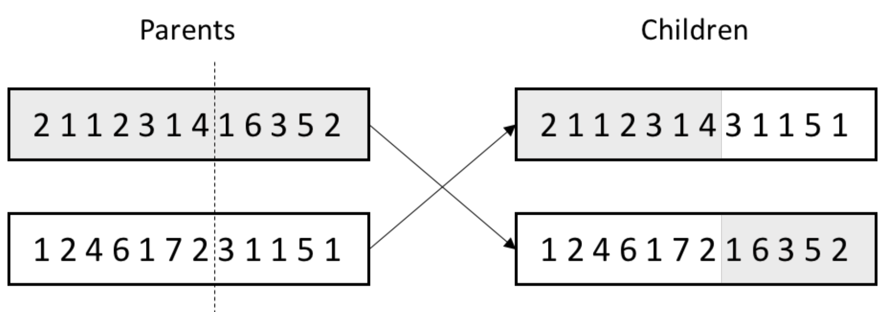

Figure 2.6 Example of crossover

Mutation randomly modifies a gene of an individual solution as illustrated in Figure 2.7. Mutation helps avoiding a premature convergence and maintaining a global search. The mutation rate is determined by a user at the beginning of the algorithm. After the mutation, the solutions form a new generation for the next iteration, and the whole process is repeated until the stopping criteria is met [69]. The process of the GA is shown in Figure 2.8.

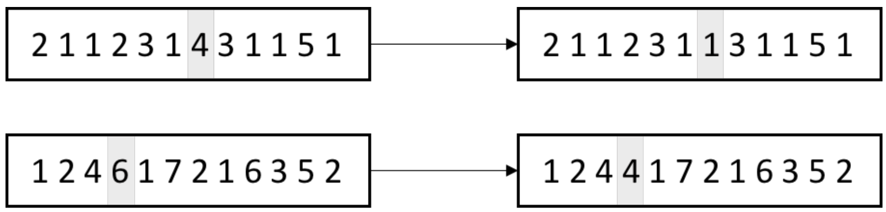

Figure 2.7 Example of mutation

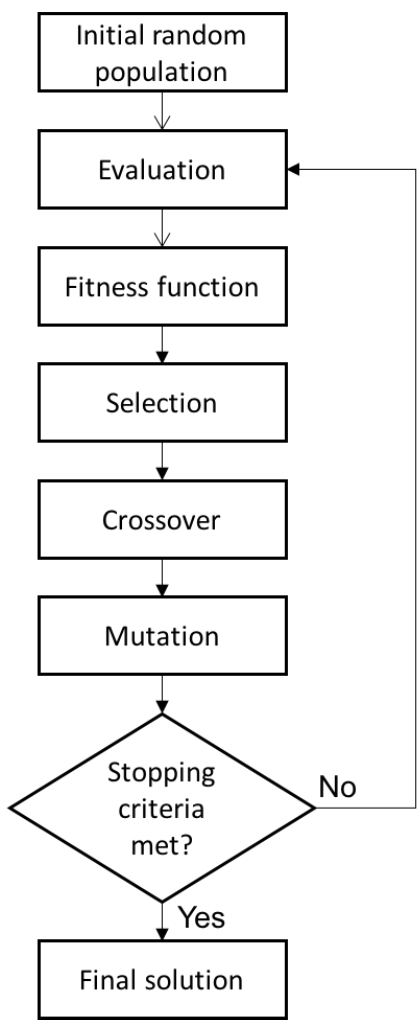

Figure 2.8 Simple genetic algorithm process

Currently, GAs are the most dominantly used optimization algorithm in the building optimization research field. GAs have many practical uses, including the optimization of building shape [7,22,74], building envelop features [27,47,75,76], and HVAC systems design and control [40,41,43,46,77,78]. The selection of algorithms depends on each study's characteristics, and there is no single best algorithm for all problems. The success of the chosen algorithm in cost and/or energy reduction relies not only on the nature of the algorithm but also on parameter settings [59]. Nevertheless, some studies claim that the GA has a higher performance than other optimization algorithms.

The main reasons for the popular use of the GA in building optimization research are: the GA (1) can deal with both continuous and discrete variables, (2) can simultaneously evaluate multiple individuals in a population that enables parallel simulations on multi-processor computers, (3) is suitable for multi-objective optimization problems, and (4) has a reduced chance of getting stuck at a local minimum [18]. Because building optimization problems have both continuous (e.g. design parameters) and discrete variables (e.g. building components), the ability to handle both variables is a very important feature of an algorithm to be used in building optimization research. The second reason is related to the efficiency of the algorithm. Existing studies show that the GA is able to produce an optimal solution within an 0.4% of accuracy with fewer simulations, i.e. 40% of the PSO and 60% of the sequential search technique [69]. This is particularly evident when a large number of parameters are involved, which is a typical case of building problems. The capability of solving multi-objective problems is also essential as, in many cases, building optimization problems need to deal with multiple conflict objectives, let's say energy savings and cost reduction [18]. The GA receives widespread support in the light of avoiding being stuck at a local optimum. Unlike other stochastic optimization methods such as sequential search and PSO, the GA prevents ending up converged at a local optimum. As the GA considers multiple points in the search space using population, instead of focusing on one potential solution, it reduces the chance of converging to a local optimum [16,58,68,69]. Because of the applicability and appropriateness of the GA to building optimization research, this study intends to use the GA as an optimization algorithm to optimize building envelop features for the minimum life cycle cost.

2.2.4 Building energy optimization tools

Building energy optimization tools can be classified into three categories in terms of the relationship between simulation and optimization: (1) stand-alone optimization tools, (2) optimization engine oriented tools, and (3) simulation-based optimization tools. Stand-alone optimization engines are embedded with optimization algorithms, but do not have a built-in energy simulation program. GenOpt, MATLAB Optimization Toolbox, modeFRONTIER, and Topgui are examples of stand-alone optimization tools. Optimization engine oriented tools are developed based on optimization engines and have an imported energy simulation program. GENE_ARCH, MOBO, jEPlus+EA, MultiOpt 2 are included in this group. These tools are more user friendly compared to stand-alone optimization tools. Simulation-based optimization tools are developed based on energy simulation programs, and the energy simulation is tightly coupled with an optimization engine. Examples are DesignBuilder optimization module, BEopt, and Opt-E_Plus. Tools in this group have the highest learnability among the three categories stated above [16,17].

Tian et al. compare seven optimization tools (four optimization engine oriented and three simulation-based) using four assessment criteria including "data completeness," "interoperability," "optimization parameters," and "post-processing capability." In general, simulation-based optimization tools are assessed to be superior in data completeness, interoperability, and post-processing capability. Optimization engine oriented tools are evaluated to be more powerful in terms of optimization capability but are not as easy to learn and use as simulation-based tools [17].

Based on literatures, GenOpt and MATLAB Optimization Toolbox are currently the most widely used optimization tools among building optimization researchers [18]. Hani and Koiv use GenOpt to optimize building envelop features of an office building in warm summer continental climate [15], and Djuric et al. also use GenOpt to optimize the building envelop insulation in addition to design and control of the hydronic heating system in a school building [52]. The MATLAB environment was used by Bornatico et al. for optimization of solar thermal system sizing for a mid-sized single-family house in Zurich, Switzerland [71]. Tuhus-Dubrow and Krarti use MATLAB as well for building shape optimization for residential buildings [7].

Some studies use tailor-made programming using C++, Cygwin, Java, R, and Visual Studio for optimization instead of using ready-made optimization package

[16]. This research uses a tailor-made optimization program developed by using C++ and a genetic algorithm (GA), and the program exchanges data with EnergyPlus[2]. The reason for using a tailor-made optimization program is due to the limitations of available ready-made optimization tools. First, algorithm selection is limited. This study intends to use a GA as an optimization algorithm, however, optimization tools usually use optimization algorithms other than GAs, such as Hooke-Jeeves algorithm, generalized pattern search methods, particle swarm optimization algorithm, and simplex algorithm. Second, selectable objective functions are limited. Some tools provide multi-objective functions, but others only allow single-objective functions. Additional limitations include building type and location. For example, BEopt is a residential building optimization tool while Opt-E-Plus is developed for commercial building optimization. Also, BEopt is limited to be used only for North American context [16].

[2] EnergyPlus is the most widely used simulation program in building optimization research, because of its strong capability of energy simulation and the text-based format of input/out files that are applicable to be coupled with optimization algorithms [18].

CHAPTER 3

DECISION THEORY

This chapter explores decision theory and discusses various decision-making criteria to find the most appropriate one to be used to make a robust decision from results of the simulation-based optimization that is conducted in this research. After conducting building optimization analyses, the next step is to make a decision to select a set of building elements (e.g. insulation, glazing, energy supply systems, appliances, lighting devices) for an energy-efficient building. However, due to uncertainties in parameters as well as in the simulation-based optimization process itself, risks exist in choosing options. The uncertainty issue in simulation-based optimization and its sources will be discussed in Chapter 4. Employing decision theory would be a good solution to cope with the risks and to make decisions that are robust to the uncertainties.

In fact, risks exist in all capital investment decision-making, including building problems, to a greater or lesser degree. This can be minimized by choosing the best decision model [79]. The goal of decision theory is to help choose the best model among all possible alternatives under the circumstance that consequences cannot be completely predicted, mainly because they are dependent on future of unknown states of world [80].

Decision theory is a classical field of research that has been actively studied in many academic fields, such as philosophy, economics, mathematics, psychology, sociology, and political science [81], but is relatively newly introduced in building research. Attia et al. develop a simulation-based decision tool to support zero-energy building design in early design stages [30]. Hopfe et al. use building performance simulation and sensitivity analysis to find more influential input parameters. In their research, analytical hierarchy process (AHP) was used to make a rational decision [82]. The AHP method is also used in other studies to develop a comprehensive indicator of indoor environment assessment [83], to select intelligent building systems [84], and to develop a housing performance evaluation model for multi-family residential buildings [85]. AHP is one of the most widely used decision-making techniques, but uncertainties are not taken into consideration in the AHP method. Another widely known approach is Bayesian decision theory; Kim and Augenbroe apply a multi-criterion assessment under uncertainty using Bayesian decision theory to support decision-making of choosing a ventilation operation strategy in hospital isolation rooms [86]. Booth and Choudhary utilize Bayesian multi-attributable utility theory to select cost-effective retrofit measures for existing UK housing stocks under the uncertainties in the prediction of energy savings from the retrofit measures [87]. Kim et al. present a multi-criteria decision-making framework by using a multi-attribute utility theory with Bayesian inference for choosing an HVAC system for a library building [88]. The Bayesian approach is a complex analysis and requires a high computational cost. It also needs a lot of information. Huang et al. introduce the simple multi-attribute rating technique

(SMART) to determine the optimal HVAC system design under multiple criteria, such as economic performance, energy performance, thermal performance, and environmental performance [89]. Rysanek and Choudhary apply non-probabilistic decision rules to a building energy retrofit project. Uncertainties in this research are divided into the optimistic or pessimistic conditions. For some variables such as physical properties, information about their probabilistic distributions is available, while others (e.g. energy price projections) do not have available probabilistic distributions; energy price projections are categorized into low, central, and high scenarios without providing information about how likely it is that each scenario will happen [8].

Most of these studies did not take into account the uncertainties and the risk attitude of decision makers in decision-making [82]. Hopfe et al. integrated uncertainty in input parameters of building design, but they made a choice between only two options (pre-chosen HVAC system designs) [82]. Their approach is comparatively simple compared to this study in which five building design parameters are optimized while integrating uncertainties in user behavior-related input variables. There currently is little information on building optimization research under uncertainty that employs decision theory to support robust decision-making.

3.1 Introduction of Decision Theory

3.1.1 What is decision theory?

Decision theory refers to a collection of methodologies and principles that are used to make a decision among a group of alternative choices. Mathematical and statistical methodologies are applied to provide information supporting decision-making [79]. Thus, decision theory is defined as "a procedure that takes account of all available information to give us the best possible logical decision" (pp.200-201) [90].

Researchers in different disciplines have endeavored to create models to explain 'how decisions should be made' and 'how decisions are actually made.' The former can be expressed as 'rational' or 'ideal' decision-making from the theoretical point of view of philosophers, economists, and mathematicians; the latter can be seen as 'everyday' decision-making from the empirical point of view of psychologists, sociologists, and political scientists. This is one way to group decision models into normative and descriptive approaches [81]. Another way to group decision models is according to the environments of certainty, risk, and uncertainty. Decision-making models under different decision environments will be discussed more in depth later in this chapter.

3.1.2 Elements of decision theory

Decision theory has three primary elements: *alternatives*, *states of nature*, and *payoffs* [79].

(1) *Alternatives* are often called *choices* or *strategies*. These are the independent decision options that a decision maker can choose in a decision theory model. For example, alternatives can be “to bring an umbrella” and “not to bring an umbrella.”

(2) *States of nature* are independent future situations that are expected to occur. One popular example is “rain” or “no rain” in the to-bring-or-not-to-bring-an-umbrella problem (See Table 3.1).

(3) *Payoffs* are dependent parameters that are a result of the combination of a chosen alternative and an individual state of nature. In other words, payoffs can be said to be a reward that a decision maker will receive as a result of the decision that he or she made and a state of nature that actually occurs. In the example shown in Table 3.1, if a decision maker decides to bring an umbrella and it turns out to be raining, the person’s bag will be heavy, but the person will stay dry.

Table 3.1 Example of a payoff table with the three decision theory elements

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">States of Nature</td></tr>
<tr><td>Rain</td><td>No rain</td></tr>
<tr><td rowspan="2">Alternatives</td><td>Umbrella</td><td>Heavy / Dry</td><td>Heavy / Dry</td></tr>
<tr><td>No umbrella</td><td>Light / Wet</td><td>Light / Dry</td></tr>
</table>

3.1.3 Decision environments

Decision-making occurs in the three types of environments that are *certainty*, *risk*, and *uncertainty* [79].

(1) *Certainty* is the environment in which a decision maker clearly knows available alternatives and their consequent payoffs.

(2) *Risk* is the environment in which partially known information is available in a probabilistic manner. In some cases, though we do not certainly know the outcomes of available alternatives, it may be known how likely the outcomes would be; that is to say, a probability of each state of nature is known. For example, there is a 20% chance of rain or 80% chance of sunshine for the weather tomorrow.

(3) *Uncertainty* is the environment in which no known information is available about the likelihood of occurrence of each state of nature. In other words, the probability of an event is completely unknown. For instance, in their research, Rysanek and Choudhary use the energy price projections from the UK Department of Energy and Climate Change, and the projections are categorized into low, central, and high scenarios without providing how likely it is that each scenario will happen [8].

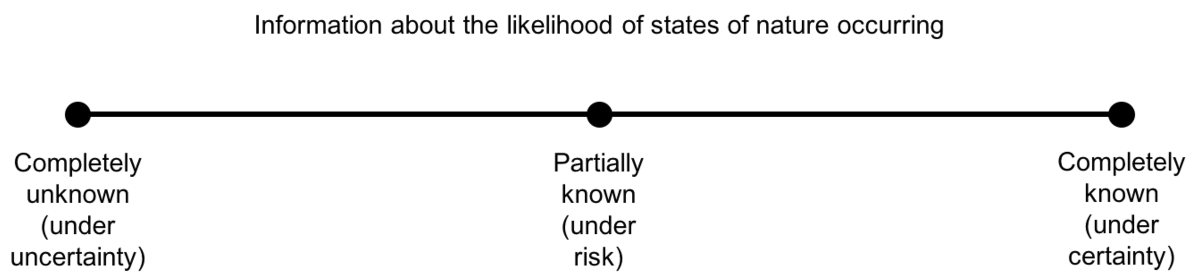

Figure 3.1 Decision environments

There are various decision-making methodologies that have different decision environments, thus it is important to choose a method appropriate to the goal and elements of a decision-making problem.

3.2 Decision-Making Under Certainty

Decision-making approaches under certainty require perfectly known information about all related parameters and outcomes, or at least assume they are completely known. It is fairly unrealistic, since such certain environment is rare in reality. Therefore, decisions made by using these decision-making rules are vulnerable to uncertainties. This research aims to include uncertainty in simulation-based optimization into decision-making, and thus decision-making under certainty is beyond the scope of this study. The maximax criterion and maximin criterion are included in this category, and they will be discussed later in '3.4 Decision-Making Under Uncertainty.'

3.3 Decision-Making Under Risk

The term *risk* is used to “describe situations for which probabilities are available to describe the likelihood of various events or outcomes” (p.256) [91]. Under the risky environment, there is therefore some available information about states of nature occurring, and it is sufficient to assign probabilities to each state of nature. Probabilities are an essential element of decision-making under risk problems, and the sum of the probabilities assigned to each state of nature must add up to one. The most popular example is flipping a coin[3]; a head or a tail are two possible outcomes, and the probability of each is 0.5, which makes the sum of all probabilities is 1.0 [79].

There are two sources of probabilities: objective or subjective. Objective probabilities are acquired from experimental observation of historical behavior or by using a statistical method and should be measurable; therefore, it is assumed that the same pattern of the probability of past events or experiments will be repeated in the future, and that the observed probabilities are stable. Also, the sample size should be adequately large enough to represent the past behavior. Subjective probabilities, on the other hand, are obtained from human judgment (e.g. experts’ best guess) about the future states of nature; hence, it is assumed that the experts have sufficient knowledge to make reasonably accurate judgment [79,91].

[3] A fair coin is assumed, that is to say the probability of a head or a tail is equally likely.

3.3.1 Expected value criterion

The expected value criterion is widely known as expected utility theory (more precisely, probability-weighted utility theory), and it has been acting as a reference standard for decision-making [92,93]. The basic concept of the expected value criterion is to choose an alternative that maximizes the expected value of the resulting utility, by multiplying the assigned probabilities of each state of nature and quantitative utilities of each payoff [80,94]. The best payoff can either be the largest or the smallest one according to the nature of payoffs; if the decision-making problem is about making profit, the best payoff would be the largest one, whereas, if the decision problem is about cost, the best would be the smallest [79].

An example of investment decision-making is summarized in Table 3.2. The states of nature have four different cases of economic states during the year and probabilities of each economic state are given. The actions are the alternatives among which a decision maker can select. Payoffs shown in percentage indicate the rates of return of each action under each state of nature [95]. The expected values of each alternative are calculated as:

Bonds: 12%(0.15) + 8%(0.2) + 7%(0.45) + 3%(0.2) = 7.15%

Stocks: 15%(0.15) + 9%(0.2) + 5%(0.45) + (-2%)(0.2) = 5.9%

Deposit: 7%(0.15) + 7%(0.2) + 7%(0.45) + 7%(0.2) = 7.0%

Since the expected value criterion chooses an alternative that maximizes the expected utility, a decision maker will select bonds at a 7.15% of expected return.

Table 3.2 Investment decision-making table [95]

		States of Nature and Probabilities			
		Growth (0.15)	Medium Growth (0.2)	No Change (0.45)	Recession (0.2)
Actions	Bonds	12%	8%	7%	3%
	Stocks	15%	9%	5%	-2%
	Deposit	7%	7%	7%	7%

The theory of utility uses concepts of lotteries and prizes for the utility function, and the "expected value" property helps understand and evaluate complex lotteries. There are four utility axioms based on the four assumptions on which the theory is founded [90]:

(1) The possible outcomes (prizes) can be compared according to a decision-maker's preferences, and the preferences should be transitive, i.e.,

$$A > B, B > C \text{ implies } A > C$$

$$A \sim B, B \sim C \text{ implies } A \sim C.$$

when,

$>$ means "is preferred to, "

$\sim$ means "is indifferent to. "

(2) Preferences for prizes and preferences for lotteries that involve the prizes should be assigned equivalently, i.e., if $A > B$, then $(P, A; 1 - P, B) > (P', A; 1 - P', B)$ if and only if, $P > P'$.

when,

P is the probability to receive prize A, and $0 < P < 1$.

(3) It is assumed that the lottery itself does not have any intrinsic reward; there is "no fun in gambling," and it is indifference whether you gamble on lotteries once or twice. Only the reward of the lottery matters. This can be expressed as,

$$(P, A; 1-P, (P', B; 1-P', C)) \sim (P, A; P'-PP', B; 1-P-P'+PP', C)$$

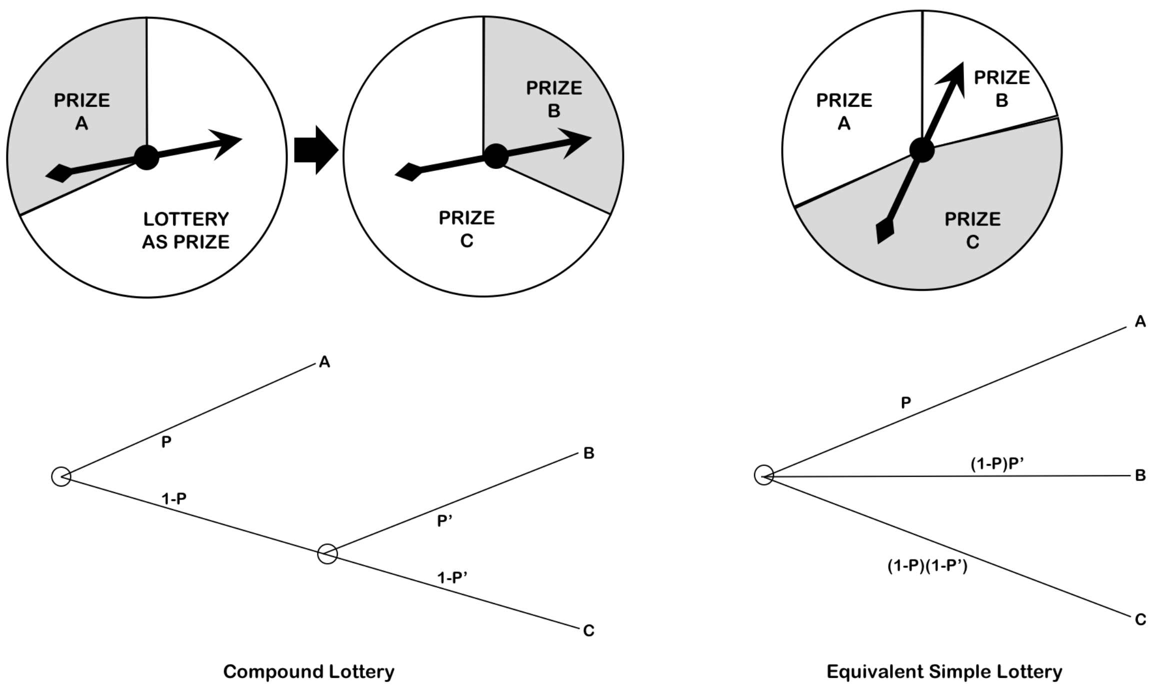

Figure 3.2 "No fun in gambling" [90]

(4) There is a continuity assumption; a certain probability P exists, which makes receiving prize C indifferent to the lottery between A and B, when $A > C > B$, i.e., $C \sim (P, A; 1-P, B)$.

Based on the assumptions above, the utility function $u(\cdot)$ of the expected value property can be articulated as [90]:

$$u(A) > u(B) \text{ if and only if } A > B$$

if $C \sim (P, A; 1 - P, B)$,

$$\text{then } u(C) = P \cdot u(A) + (1 - P) \cdot u(B)$$

The expected utility has been the most popular tool for decision analyses under risk. However, expected utility theory is often criticized for not explaining how rational individuals *really* make choices under uncertainty. Rather, it explains how rational individuals *should* make choices under uncertainty [93].

3.3.2 Expected opportunity loss criterion

People do not always make decisions to maximize the expected utility. Utility theory assumes a rational decision maker who aims to make the maximum utility at all times, but it leaves little room for emotions. However, in everyday-lives in the real world, choices often involve emotions such as regret, rejoice, and rewards, that are typically considered irrational from the perspective of utility theory [96]. In other words, our choices in real-life can be very different from what rational decision theory suggests, in some circumstances. This psychological part can be explained by the expected opportunity loss criterion, for instance, regret theory. "Regret" refers to the painful sensation of recognizing that a decision maker could have chosen a better alternative than the one he or she already chose. "Rejoice" is the opposite experience of recognizing that one has chosen a more favorable alternative [92]. The amount of regret is determined as "the difference in value between the assets actually received and the highest level of assets produced by *other* alternatives" (p.963) [97]. According to regret theory, people make decisions based on the utility outcome as well as quantity of regret [98]. Therefore, the utility $u_E(x)$ depending on emotion E in the regret model can be expressed as [99]:

$$u_E(x) = u_P(x) + r_E$$

where

$u_P(\cdot)$ = monotonically increasing value function

x = the outcome from the chosen alternative

r_E = an offset depending on regret or rejoice (negative for regret and positive for rejoice)

In so doing, regret theory is able to explain people's paradoxical behavior such as one person gambles (risk-prone behavior) and buys an insurance (risk-averse behavior) at the same time. If one thinks about betting on a horse, but does not actually bet, it would be regretful to see the horse win at the next race, so one gambles on the horse in order to avoid regret. Likewise, one buys insurance because he or she does not want to feel regret from seeing his or her house burn down after choosing not to have insurance [92].

Therefore, the expected opportunity loss criterion takes the emotion of regret into account in decision-making. The expected opportunity loss refers to what a decision maker will lose if the chosen alternative is not the best payoff under a state of nature. Thus, the opportunity loss values are calculated as the difference between the best possible payoff under each state of nature and all other payoffs under that state of nature. The determined opportunity loss values are multiplied by their attached probabilities and then added to make expected opportunity loss values for each alternative. At last, the alternative with the minimum expected opportunity loss is selected [79]. For example, from the same investment decision-making problem explored in the expected value criterion (Table 3.2), opportunity loss values for each alternative under each state of nature are computed as shown in Table 3.3. First, determine the best payoff under each state of nature, which is 15% under growth, 9% under medium growth, 7% under no change, and 7% under recession. Second, subtract other payoffs under the same state of nature from these best payoffs; this makes an opportunity loss table (Table 3.3). Then, by using the computed opportunity loss values and the probabilities, expected opportunity loss values are computed (Table 3.4). Finally, an individual who makes an investment decision under the expected opportunity loss criterion will invest in bonds that have the smallest expected opportunity loss value at 1.45%.

Table 3.3 Opportunity loss table

		States of Nature and Probabilities			
		Growth (0.15)	Medium Growth (0.2)	No Change (0.45)	Recession (0.2)
Actions	Bonds	15-12=3%	9-8=1%	7-7=0%	7-3=4%
	Stocks	15-15=0%	9-9=0%	7-5=2%	7-(-2)=9%
	Deposit	15-7=8%	9-7=2%	7-7=0%	7-7=0%

Table 3.4 Expected opportunity loss solution to the investment decision-making problem

		States of Nature and Probabilities				Expected Opportunity Loss
		Growth (0.15)	Medium Growth (0.2)	No Change (0.45)	Recession (0.2)	
Actions	Bonds	3(0.15)	1(0.2)	0(0.45)	4(0.2)	**1.45%**
	Stocks	0(0.15)	0(0.2)	2(0.45)	9(0.2)	2.7%
	Deposit	8(0.15)	2(0.2)	0(0.45)	0(0.2)	1.6%

3.3.3 Limitations

Some assumptions of the expected value criterion are against human instinct. According to the expected value criterion, which is the most widely used decision theory, people make decisions based on the expected value. This decision rule does not account for emotions, such as regret and rejoice, that are considered irrational from the viewpoint of the expected value criterion. However, in reality, people do not make decisions depending solely on the utility. There is a saying that "people are not logical. They are *psycho*logical" (p.2) [100]. This is why the expected value criterion cannot explain several popular paradoxes, for example, Allais' criticism [96,97].

Allais' paradox is a widely known criticism against the expected utility paradigm. It shows people's actual choice between a small certain gain and a larger uncertain gain is contradictory to the claim of the expected utility theory to maximize the expected value. There are two situations each of which has two lottery options (Figure 3.3).

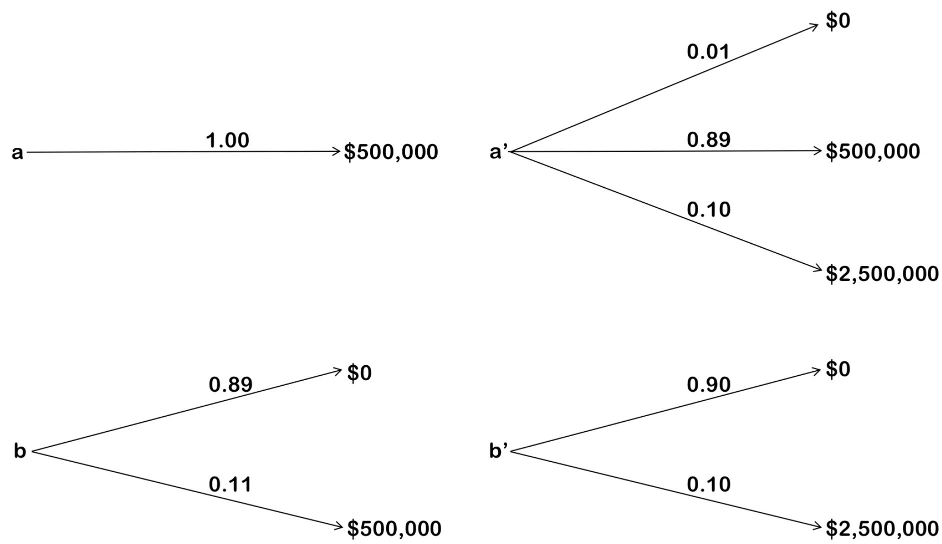

Figure 3.3 Allais' paradox [80]

A decision maker can choose between lotteries a and a', and then between lotteries b and b'. Lottery a has a certain reward of $500,000, while lottery a' has a 10% chance of winning $2,500,000, an 89% chance of winning $500,000, but an 1% chance of gaining nothing. Between these two options, most people prefer a to a', because it does not make sense for them to have risk of getting nothing for a *very large* fortune instead of an assured *large* fortune. However, most of the same people prefer b' to b, when lottery b has an 11% chance of winning $500,000 and an 89% chance of gaining nothing while lottery *b'* has a 10% chance of winning $2,500,000 and a 90% chance gaining nothing; because there is nearly no difference between the chances of getting a large fortune and a very large fortune, they do not sacrifice the amount of reward owing to little difference. This is not compatible with the utility concept because a utility function must satisfy both of the following equations at the same time, and there cannot be such utility function [80,81,93]:

$$u(\$500{,}000) > 0.1u(\$2{,}500{,}000) + 0.89u(\$500{,}000) + 0.01u(\$0)$$

$$0.11u(\%500{,}000) + 0.89u(\$0) < 0.1u(\$2{,}500{,}000) + 0.9u(\$0).$$

Another criticism to the expected utility concept is about the transitivity assumption. A decision maker wants to paint his room green. He has three shades of green, g_1, g_2, and g_3. The shade g_1 is slightly darker than g_2, and g_2 is slightly darker than g_3. When he first sees g_1 and g_2, he does not recognize the difference in shade, so for him, the two shades are indifferent, that is, $g_1 \sim g_2$. He also cannot tell the difference between g_2 and g_3, so they are again indifferent to him, that is, $g_2 \sim g_3$. Finally, when he sees g_1 and g_3 together, he can distinguish between the two shades and prefers g_1 to g_3, that is, $g_1 > g_3$. This apparently violates the assumption of transitivity, because $g_1 \sim g_2$, $g_2 \sim g_3$ implies $g_1 \sim g_3$ [93].

Some of the criticisms are resolved by subsequent behavioral decision theories including regret theory. Regret theory is an important decision theory under risk, and it explains quite well real-world decision-making problems that are inconsistent with the expected utility. However, regret theory intrinsically assumes the risk-averse attitude of decision makers [96,98].

The most obvious disadvantage of the expected value criterion and the expected opportunity loss criterion is that both of them are probabilistic decision theories, and these criteria require a lot of information to determine the decision solution. Probabilities of states of nature are the essential element to utilize these decision rules under risk, but probabilities are not always known or are limitedly available. This causes a limited use of probabilistic decision rules.

3.4 Decision-Making Under Uncertainty

Unlike risky situations, if the probabilities “cannot be quantified, or if the events themselves are unpredictable” (p.256) [91], this decision environment is called *uncertainty*. Under this environment, there is little information about states of nature; it is not sufficient to assign probabilities of occurring to each state of nature. Nevertheless, types of existing states of nature, available alternatives, and payoffs of each alternative under each state of nature are known. A decision maker just does not know how likely it is that each state of nature will take place [79].

3.4.1 Maximax criterion

The maximax criterion is a very optimistic decision-making rule that aims to choose the best (maximum) one among the payoffs of all available alternatives in all given states of nature. Hence, the steps of decision-making under the maximax criterion is, first, to find the best payoff for each alternative, and then, find the maximum payoff among them [79].

To demonstrate this criterion, let’s revisit the investment decision-making problem shown in Table 3.2. The solution to this problem under the maximax criterion is presented in Table 3.5. First, select the maximum payoff for each alternative, that is to say, 12% for bonds, 15% for stocks, and 7% for deposit. Then, select the best number among the maximums, which is 12%. Therefore, according to the maximax criterion, the decision maker would decide to invest in stocks expecting a 15% of return.

Table 3.5 Maximax solution to the investment decision-making problem

		States of Nature				Maximum Payoff	Maximum of Maximums
		Growth	Medium Growth	No Change	Recession		
Actions	Bonds	**12%**	8%	7%	3%	12%	15%
	Stocks	**15%**	9%	5%	-2%	**15%**	
	Deposit	**7%**	**7%**	**7%**	**7%**	7%	

3.4.2 Maximin criterion

The maximin criterion is a semi-pessimistic decision-making rule and also known as Wald's criterion. It assumes that a globally pessimistic condition is going to occur and selects the maximum value out of it. Thus, it selects the best one among the group of the minimum payoff of each alternative [8,79,92].

Using the same investment decision-making problem presented in Table 3.2, the solution under the maximin criterion is given in Table 3.6. First, choose the minimum payoff for each alternative, i.e., 3% for bonds, -2% for stocks, and 7% for deposit. Then, choose the best one among these minimums, which is 7%. Therefore, according to the maximin criterion, the decision maker would decide to choose deposit as his or her investment strategy.

Table 3.6 Maximin solution to the investment decision-making problem

		States of Nature				Minimum Payoff	Maximum of Minimums
		Growth	Medium Growth	No Change	Recession		
Actions	Bonds	12%	8%	7%	**3%**	3%	7%
	Stocks	15%	9%	5%	**-2%**	-2%	
	Deposit	**7%**	**7%**	**7%**	**7%**	**7%**	

3.4.3 Laplace criterion

The Laplace criterion assumes an equally likely chance of occurring for all possible states of nature. Thus, an equal probability can be assigned to each state of nature. For the given investment decision-making problem, for example, each state of nature (i.e. growth, medium growth, no change, and low) has an equal probability to occur, that is 25%. The next step is to calculate an expected value of each alternative using the assigned probabilities, and select the best expected value [79].

The Laplace solution to the investment decision is presented in Table 3.7. First, an equal probability of 25% is given to all states of nature. An expected value for each alternative is computed using payoffs and the probability; the computed expected values are 7.5% for bonds, 6.75% for stocks, and 7% for deposit. Thus, a decision maker who uses the Laplace selection will decide to invest in bonds.

Table 3.7 Laplace solution to the investment decision-making problem

		States of Nature and Probabilities				Expected Value
		Growth **(0.25)**	Medium Growth **(0.25)**	No Change **(0.25)**	Recession **(0.25)**	
Actions	Bonds	12%	8%	7%	3%	**7.5%**
	Stocks	15%	9%	5%	-2%	**6.75%**
	Deposit	7%	7%	7%	7%	**7.0%**

3.4.4 Hurwicz criterion

The Hurwicz criterion is also called ‘criterion of realism’ and ‘optimism-pessimism index’ because it is in the middle of maximax optimism and maximin pessimism [92]. The Hurwicz criterion allows the decision maker's personal view of the degree of optimism or pessimism on states of nature. This personal view is presented as the 'coefficient of optimism' (or Hurwicz index) on a scale from 0 to 1 and represented by the Greek letter α (or *H*). The larger the coefficient of optimism, the more optimistic the decision maker's view about the future. Thus, the Hurwicz selection starts with choosing the value of *H* according to the decision maker's subjective degree of optimism. Then, determine the maximum and minimum payoffs for each alternative, and weight the maximum and minimum payoffs by multiplying the coefficient of optimism (*H*) and the coefficient of pessimism (1 - *H*), respectively by the maximum and the minimum. The two weighted maximum and minimum are added to earn the expected value for each alternative. Finally, select the best expected value [8,79].

From the same example of the investment decision-making problem, if a decision maker is comparatively optimistic and lets *H* = 0.7, the expected values for the three given alternatives are calculated as:

Bonds: 12%(0.7) + 3%(1 – 0.7) = 9.3%

Stocks: 15%(0.7) + (-2%)(1 – 0.7) = 9.9%

Deposit: 7%(0.7) + 7%(1 – 0.7) = 7.0%

Thus, according to the Hurwicz criterion, a decision maker would choose the best expected payoff which is stocks at 9.9% of return as one's investment decision. In contrast, if a decision maker has a fairly pessimistic point of view and lets *H* = 0.3, the expected values for the alternatives are computed as:

Bonds: 12%(0.3) + 3%(1 – 0.3) = 5.7%

Stocks: 15%(0.3) + (-2%)(1 – 0.3) = 3.1%

Deposit: 7%(0.3) + 7%(1 – 0.3) = 7.0%

The decision maker would select deposit since it has the best expected payoff at 7.0%. It is notable that the overall expected values calculated with a smaller H (pessimism) are fairly smaller than those calculated with a larger H (optimism), except the case of deposit that has the same payoff under all states of nature.

Table 3.8 Hurwicz solution to the investment decision-making problem (H = 0.7)

		States of Nature				Expected Value
		Growth	Medium Growth	No Change	Recession	
Actions	Bonds	12%	8%	7%	3%	**9.3%**
	Stocks	15%	9%	5%	-2%	**9.9%**
	Deposit	7%	7%	7%	7%	**7.0%**

Table 3.9 Hurwicz solution to the investment decision-making problem (H = 0.3)

		States of Nature				Expected Value
		Growth	Medium Growth	No Change	Recession	
Actions	Bonds	12%	8%	7%	3%	**5.7%**
	Stocks	15%	9%	5%	-2%	**3.1%**
	Deposit	7%	7%	7%	7%	**7.0%**

A decision maker's optimistic or pessimistic view on states of nature is often linked to one's risk-taking attitude. A risk seeker is willing to take extra risks desiring a chance of winning a higher return, while a risk-averse decision maker always tries to avoid taking risks and aims at looking for the least risky outcome. Thus, a risk seeker is regarded to have a larger coefficient of optimism whereas a risk-averse agent is considered to have a smaller coefficient of optimism. A risk-neutral person does not take risks into account when making a decision. The coefficient of optimism is assumed to be 0.5 for the risk-neutral case. As we can see in Tables 3.8 through 3.10, a decision made under the Hurwicz criterion can vary in accordance with the decision maker's view of optimism.

Table 3.10 Hurwicz solution to the investment decision-making problem (H = 0.5)

		States of Nature				Expected Value
		Growth	Medium Growth	No Change	Recession	
Actions	Bonds	12%	8%	7%	3%	**7.5%**
	Stocks	15%	9%	5%	-2%	**6.5%**
	Deposit	7%	7%	7%	7%	**7.0%**

The major advantage of the Hurwicz criterion is that a decision maker's subjective view of optimism or pessimism on states of nature in the future can be adjusted by changing the value of the coefficient of optimism (H) 0 through 1.

3.4.5 Minimax criterion

The minimax criterion is also known as Savage's regret criterion. It is also called "minimax regret," "minimax risk," and "minimax loss" [92]. It has something in common with the expected opportunity loss criterion as it attempts to minimize regret that is caused from making a non-optimal decision. The difference is that the minimax criterion does not require probabilities of states of nature. Regret is determined as the expected opportunity loss between the best possible outcome and the actual outcome, and computed by subtracting each payoff from the best payoff under each state of nature, respectively. Thus, the best possible expected opportunity loss is 0, and larger values indicate greater regret. For example, from the same investment decision making problem, the best payoff under economic growth is 15% when choosing stocks, and the expected opportunity loss for each alternative under economic growth can be computed as:

Bonds: 15 – 12 = 3%

Stocks: 15 – 15 = 0%

Deposit: 15 – 7 = 8%

When all the expected opportunity losses for each alternative and state of nature are calculated, determine the maximum opportunity loss for each alternative, then select the minimum value [79,95,101]. Table 3.11 shows the minimax solution, and the investment decision made under the minimax criterion to minimize regret would be bonds.

Parmigiani and Inoue explain the minimax criterion providing an analogy with game theory[4]. They assume that decision-making is a zero-sum two-person game between a statistician and nature. Because nature chooses first, it is best for the statistician to assume the worst scenario and try to minimize the maximum loss [80]. In this light, decision-makers pursue the minimization of the risk (or regret) between the best and the worst outcomes. As a result, the chosen option is the least sensitive to changing scenarios [8]. Hence, under the minimax criterion, one might

[4] Decision theory and game theory are both about making decisions, but the principal difference is that decision theory involves an individual agent while game theory involves multiple players and their choices have impact on each other's decision-making.

choose an option with a smaller predicted return and a smaller uncertainty rather than an option with a larger predicted return and a larger uncertainty risk.

Table 3.11 Minimax solution to the investment decision-making problem

		States of Nature				Maximum Opportunity Loss	Minimum of Maximums
		Growth	Medium Growth	No Change	Recession		
Actions	Bonds	3%	1%	0%	**4%**	**4%**	4%
	Stocks	0%	0%	2%	**9%**	9%	
	Deposit	**8%**	2%	0%	0%	8%	

Figure 3.4 illustrates the decision-making solutions under different decision-making criteria under uncertainty (non-probabilistic decision theories) discussed above. It is noteworthy that the best decision made under different criterion varies. Since non-probabilistic decision rules assume that there is little or no information available for the probability of which state of nature is going to occur, it is the best strategy (and also natural) to rely on decision maker's view on whether the state of nature is going to be optimistic of pessimistic.

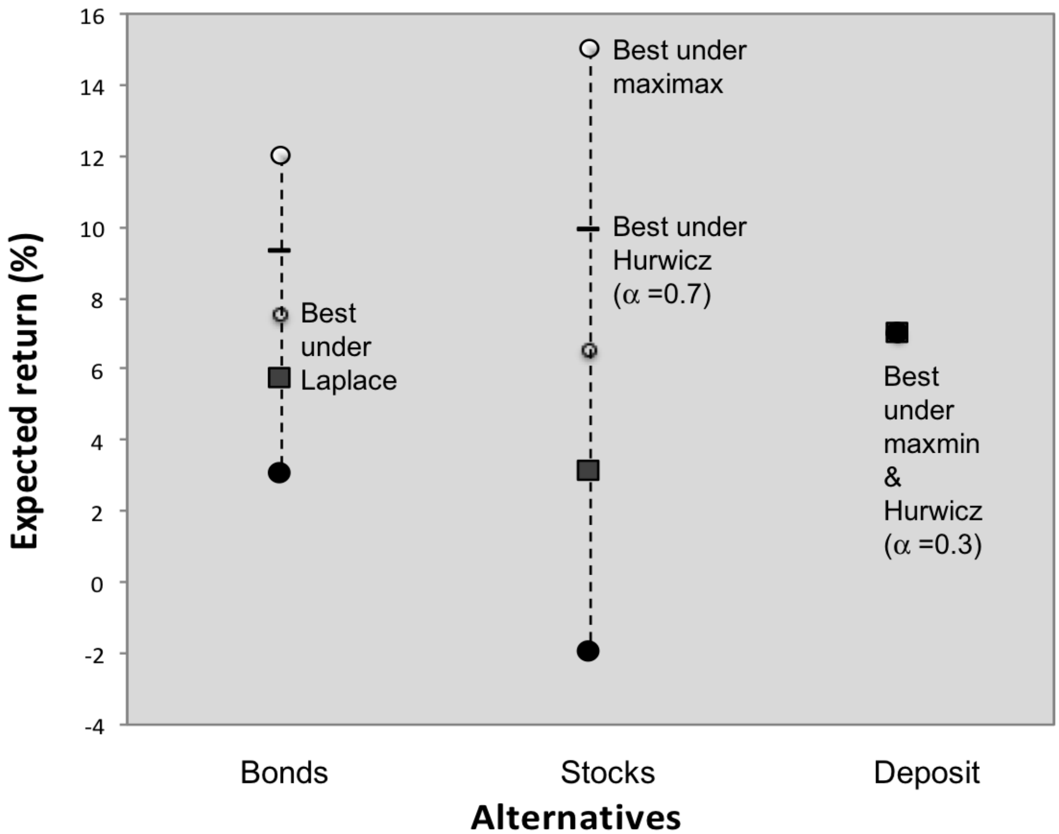

Figure 3.4 Investment decision-making solutions under maximax, maximin, Laplace, and Hurwicz criteria

3.4.6 Information-gap decision theory

The information-gap decision theory (IGDT) developed by Ben-Haim [102] is relatively recently introduced into decision and risk management science. The IGDT is intended to support decision making under severe uncertainty and does not require much information. Only nominal estimates are required [103], which are available in the form of mean, minimal, and maximal values for parameter settings used in building optimization. Hence, the IGDT can be a good candidate to be applied to research fields in which very limited information and knowledge is available for the definition of probability factors [104]. The IGDT evaluates the robustness of a design or a solution when there is a lack of available information. It identifies the designs that have performance invulnerable to the effects of uncertainty [103].

The IGDT is based on the analysis of the discrepancy between the known data input and the data that could be known [105]. Thus, the uncertainty of a design or a solution refers to the discrepancy, and is expressed as the "information-gap." Solutions with different information-gap are compared and ranked by the IGDT. The most preferred solution is the design with the maximum resistance to the information-gap.

The IGDT claims that it is a totally new theory that can substitute other classical decision-making rules under uncertainty because of its non-probabilistic nature. However, the biggest criticism against IGDT is that the theory is neither new nor radically different from classical decision-making criteria under uncertainty. It is criticized as a type of worst-case analysis and a simple instance of the maximin criterion [106].

3.4.7 Limitations

The major limitation of decision-making rules under uncertainty is that a decision maker does not know how likely it is for a state of nature to happen, but he or she still should make a decision from a set of alternatives. The decision maker does not have objective grounds for his or her optimistic or pessimistic point of view. Thus, decision making rules under uncertainty are more suitable for private decision problems. When making a public decision, a decision maker needs to have some knowledge about states of nature to predict how likely it is they will occur. If not, the decision would not be reasonable and defensible [95].

CHAPTER 4

RESEARCH SCOPE

This chapter defines the scope of this research. The deterministic and stochastic approaches are explained to find which one of these is the most appropriate for simulation-based building optimization. Various sources of uncertainty in simulation-based building optimization are also introduced and limited to a certain range in accordance with the goal of this research. Finally, specific research questions and objectives are presented.

4.1 Deterministic vs. Stochastic Approaches

Deterministic processes are defined by a single, precise quantity. When the same input data are repeatedly used for the same simulation over and over again, it will produce the exactly same result. The deterministic approach is only applicable to an ideal system that is very well known and there are no uncertain processes in it. In reality, nature itself is not deterministic, and there are numerous unknown or uncertain properties. A system can also be affected by accumulated environmental loading for a long period of time and aging [107]. Similarly, the building is a system that has various uncertain and unknown properties and can be affected by many external factors [108]. Therefore, buildings can only be realistically analyzed when a stochastic approach is implemented. Deterministic modeling has been widely used for building simulations because of the difficulty and complexity of the stochastic approach. However, deterministic models cannot be accurately used for building optimization since they do not provide statistical information [109].

4.2 Uncertainty Sources

Uncertainty is an intrinsic problem in all building simulation-based optimization problems. Sources of uncertainty have been investigated by many previous studies, but there is no firmly established categorization of uncertainty sources in computer-based simulation and modeling. Researchers use different categories with varying sources of uncertainty. This study borrows the categorization by Loucks and van Beek: (1) natural variability, (2) knowledge uncertainty, and (3) decision uncertainty [91]. Though the original reference is about the water resources system, the categorization is comprehensive and encompasses overall uncertainty sources in the simulation-based building energy optimization problem.

4.2.1 Natural variability

In building research, the main source of uncertainty in natural variability is weather data [18,110,111]. The most widely used weather data in building simulation is Typical Meteorological Year (TMY). Since TMY is based on historical weather data, that is monthly average data for nearly 30 years, it is normally assumed that a building operates under the typical weather condition [112]. However, this leads to the discrepancy between the modeled and the actual weather under which the building operates. In reality, a building may experience a much warmer or cooler summer and/or winter compared with the typical year, and this can bring about a critically different heating and cooling energy usage in the actual building from the model prediction. Also, TMY does not take into account the effect of global warming. In addition, if a building is equipped with renewable energy generation measures such as wind turbines and photovoltaic panels, wind direction and velocity as well as solar radiation are also important factors in predicting energy generation.

4.2.2 Knowledge uncertainty

Knowledge uncertainty refers to known and unknown errors in input data and is again divided into parameter value uncertainty and model structural and computational errors. Parameter value uncertainty mainly results from uncertain estimates of parameters [91]. Uncertainty may come from the physical parameters such as the building geometry (e.g. height, length, breadth, area and orientation of glazing) and thermophysical properties of materials (e.g. thickness, thermal conductivity, density, heat capacity, emissivity, absorptivity of wall, roof, and windows). Building materials are often assumed to have a fixed, deterministic value for their properties; however, even building material properties such as density, heat conductivity, and vapor permeability vary within a range and have probability distributions for their value [107]. Not only can measuring error always exist in these properties, but also other factors including moisture content, temperature, humidity, and age can affect the physical properties [88,89,111–113]. Other uncertainty regarding parameter values originate from the pre-set working conditions that are determined by designers. For example, the ventilation rate that is given by a designer during the planning process cannot be measured precisely. Heat dissipation rate of occupants cannot be determined accurately during the design stage because it depends on the type of work, gender, age, and metabolic rate of the individual occupant [89]. Uncertainty also arises from the parameters that are associated with the real-time operation of the building. These parameters are not controllable and impossible to estimate accurately during the design process. Examples are infiltration, internal heat gains from occupants, electric equipment and light, internal and external shading coefficient, HVAC systems operation (e.g. thermostat setpoint), and window use [18,88,89,110,111,113,114]. In addition, there is a gap between the actual performance and the nameplate efficiency of building facilities. It is also possible that performance of a system decreases with advancing years. There can be the risk of technical breakdowns or an inherent weakness of a system that obstructs the system's best performance [8].

Uncertainty in model output is also derived from model structural and computational errors. This is intrinsic in the model system, and "no matter how good our parameter value estimates, our models are not perfect and there is a residual model error" (p.260) [91]. It is spontaneous that the more complex the model, the more potential for errors. Hence, it is important to decide the level of complexity of a model in order to properly represent the real system but not to be too complex. Since a model cannot be identical to the real system, approximations, assumptions, and simplifications are made by numerical methods in modeling tools. This leads to model biases. Building energy simulation program capabilities are related to the choice of algorithms to calculate various heat and mass transfer processes in the building structure, such as the convection algorithm and the heat balance algorithm [18,88,91,115,116]. The processes are generally formulated with empirical assumptions using roughness coefficients to simplify the calculations. For example, the SimpleCombined method is one of the five methods that EnergyPlus provides to compute Outside Surface Heat Balance module. The equation for this algorithm is:

$$h = D + EV_z + FV_z^2$$

where

h	= heat transfer coefficient
V_z	= local wind speed calculated at the height above ground of the surface centroid
D, E, F	= material roughness coefficients

As seen in the equation above, the roughness coefficients (D, E, F) that are taken from ASHRAE Handbook of Fundamentals [117] are used in the algorithm, and these can be a source of uncertainty because the values are not accurate [112]. Estimated values of the material roughness coefficients (*D, E, F*) are given according to the degree of surface roughness from 1 (very rough) to 6 (very smooth). Table 4.1 shows the values of each roughness coefficient for each roughness index [118].

Table 4.1 Roughness Coefficients D, E, and F

Roughness index	D	E	F	Example material
1 (very rough)	11.58	5.894	0.0	Stucco
2 (rough)	12.49	4.065	0.028	Brick
3 (medium rough)	10.79	4.192	0.0	Concrete
4 (medium smooth)	8.23	4.0	-0.057	Clear pine
5 (smooth)	10.22	3.1	0.0	Smooth plaster
6 (very smooth)	8.23	3.33	-0.036	Glass

4.2.3 Decision uncertainty

The sources of decision uncertainty are related to unexpected changes in what is being modelled. Changes in nature, human goals, interests, activities, demands, and impacts are examples of uncertainty sources under this category [91]. As global warming accelerates, it is projected that the global surface temperature will continuously increase. Due to fossil fuel depletion, prices for energy depending on fossil fuels are anticipated to rise. These changes in nature have an impact on human goals for or interests in the building sector. Building codes have been evolving towards reducing energy consumption in buildings and making buildings more sustainable, for instance, net zero energy buildings. Correspondingly, what humans want or need in the future may vary from what they do now. People have wanted to have a more comfortable indoor environment while consuming a lot of energy for heating, cooling, and lighting; however, we may want free running buildings in the near future even though we need to sacrifice our comfort for energy savings because of the changing global situations.

4.3 Scope of the Thesis

Simulation-based optimization aims to find the optimal combination of parameters while achieving a single objective or multiple objectives. The success of simulation-based optimization is dependent on the accuracy of model prediction, which is dependent on the accuracy of input variables. However, there are various sources of error and uncertainty in input variables that can lead to overestimation or underestimation of building energy performance, which may result in making an inaccurate decision [110]. The complex nature of building optimization and uncertainty in input variables make simulation-based building optimization unsuitable for the deterministic approach that has been widely used in building energy problems due to its simplicity compared to the stochastic approach [109]. This research employs a stochastic approach in order to incorporate uncertainties in input variables in the process of simulation-based building optimization.

As discussed in '4.1. Deterministic vs. Stochastic Approaches,' a stochastic approach should be taken into account for building optimization research because of the buildings' stochastic nature, but it has not been commonly used due to its complexity and the difficulty in its implementation in building research problems. A Monte Carlo method is a widely used statistical method to deal with a stochastic problem with uncertain parameters, while making the problem simpler and more convenient. It is a sampling-based technique that repeats multiple model runs and uses statistical distribution of input data that were produced by random sampling to obtain output distributions [109,111,119,120]. Due to its stochastic nature, the

Monte Carlo simulation has been broadly used for the uncertainty and sensitivity analysis in building research [88,115,119,121–131]. A few building optimization studies employ a Monte Carlo technique as a part of the research, but these are also in regard to uncertainty and sensitivity analysis of parameters [108,111,132]. In this thesis, a sampling method (Latin hypercube sampling) of the Monte Carlo technique is applied as a random generator for uncertain input variables within their probability distributions.

Various uncertainty sources are introduced in '4.2 Uncertainty Sources.' There exist numerous sources of uncertainty when conducting simulation-based building energy optimization [133]. Uncertain factors such as climate, occupant behavior, and building operation are hard to measure or predict, hence causing difficulties in using computational analyses in building design to support optimal decision-making [124]. Therefore, it is essential to find a way to cope with the uncertainty in simulation and optimization. Including uncertainty in building optimization is a good way to enhance the robustness of the optimization result and to decrease risk in it [66].

However, it is impossible to deal with all uncertainty sources in the current study. Among the various uncertainty sources introduced and discussed, this research limits its scope to the user behavior-related input variables, such as occupancy/lighting/electrical appliances schedules and thermostat setpoint temperatures for heating and cooling. This is because these factors have a great influence on the uncertainties in building simulations [134,135]. Occupants' energy related behaviors play an important role in building energy use as occupants control their indoor climate in order to satisfy their needs for indoor environmental quality including thermal comfort. However, the impact of occupant behavior is currently under-recognized and over-simplified [136]. It is highly complex and difficult to predict occupants' behavior in buildings, and it inherently has uncertainty due to its stochastic nature. As the size of houses is getting bigger [2] and as the size and number of household appliances also increase, the percentage of residential energy use that is relevant to miscellaneous electricity loads and major appliances is continuously and rapidly increasing [137].

The actual energy performance of a building is dependent on occupants' energy use behaviors in the building [114,122,138,139]. Firth et al. indicate an important role of behavioral factors for energy use as they found a substantial difference in domestic heat and electrical energy consumption between similar households [138]. Gill et al. point out that there are 51%, 37%, and 11% differences in heat, electricity, and water consumption, respectively, in low-energy dwellings, resulting from energy-efficiency behaviors of occupants [139]. User behaviors are subjective and diverse, and difficult to measure and quantify. Moreover, user behavior-related parameters are typically unpredictable and uncontrollable during the design stage when most simulation and optimization works are done, so they have a greater degree of uncertainty.

The building type used in this research is the residential building, and a typical U.S. single-family home is modeled for simulation and optimization. The residential building is more appropriate for this study because user behavior-related input variables have a greater impact on household energy consumption compared to commercial buildings; residents of homes usually have more control over their indoor environment, such as adjusting thermostats and window use. They are also economically responsible for their energy use unlike occupants of commercial buildings who are generally passively exposed to their indoor environment and typically do not pay for the energy that they use [140].

4.4 Research Questions and Objectives

The principal goal of this study is to integrate uncertainties in input variables into building optimization and suggest a robust decision-making method. Consequently, this research consists of two major parts, that is, uncertainty integration in the building optimization process and robust decision-making. The objectives of this research are to (1) propose a method to cope with the uncertainties in occupant behavior-related variables of a building optimization process and to (2) introduce a decision-making technique that supports robust decision-making to reduce the risk of choosing an unlikely option from output distributions of the optimization result. This thesis, accordingly, aims to answer the following research questions:

- How can the uncertainties in occupant behavior-related input variables be integrated into the simulation-based building optimization process?
- What is the influence of integrating uncertainties in input variables on the robustness of the optimization results?
- What is a good strategy for robust decision-making from the optimization results?
- Which decision-making criterion is appropriate for the scope and elements of this study?

To answer these questions, a method to include uncertainties in input variables is proposed and evaluated. The specific research method and steps are described in the following chapter.

CHAPTER 5

RESEARCH METHOD

5.1 Overview

The research procedure of this study has three major steps: (1) probability distributions of input variables, (2) iterative process of computer simulation-based optimization, and (3) decision-making for optimal result. Figure 5.1 illustrates the work flow diagram of this research.

In the first step, the probability values of the input variables that are associated with the occupant behavior in U.S. residential buildings are defined. Input variables are investigated and prepared in the form of probability distribution to be sampled for the Monte Carlo technique. This study limits its scope to occupant behavior-related input variables, and the selected input variables with uncertainty are classified into three types: (1) the internal load intensities for individual rooms, (2) the room specific schedules, and (3) thermostat setpoint temperatures for heating and cooling. The internal load intensities and schedules for each room have three components: occupancy density, lighting, and power consumption of household appliances.

In the second step, a set of input variables is sampled by using the Latin hypercube sampling (LHS) method. Then, the sample set is used for building energy simulation using EnergyPlus. The genetic algorithm optimization is linked to the simulation and makes it repeat until an optimal solution is obtained according to the objective function (i.e. minimum life cycle cost). Since one LHS run generates 14 sample sets, this leads to 14 optimization runs that produce 14 discrete results. In this study, the results of two sampling runs (28 results in total) are combined and regarded as one output distribution to make a larger sample size. The iterative simulation-optimization process is carried out for three locations in the U.S. (Chicago, IL; Madison, WI; and Washington, D.C.) using a typical residential building. Relatively similar climates are chosen in order to verify the optimization results. Six LHS runs are performed, which give 3 output distributions, for each location.

The last step is to make a robust decision from the output distribution. Since the output distribution is made of 28 optimization results, a valid evaluation strategy is needed to support robust decision-making for selecting an optimal solution. Two types of techniques are used for the robust decision-making: (1) statistical technique and (2) decision-making criterion under uncertainty. The former is based on the frequency of recommendations from the optimization results; the more a parameter setting is recommended, the more it is considered to be an optimal solution. However, when there is little difference between the most recommended parameter setting and the second most recommended parameter setting, it may be insufficient to tell there is a significant difference between the two settings. In this case, a statistical technique which is called the 'test of proportion' is used to see if there is a statistically significant difference between the two options. If there is a statistically significant difference, the most recommended parameter setting is selected; if not, the Hurwicz criterion as a decision-making rule under uncertainty is used to choose an optimal solution between the two.

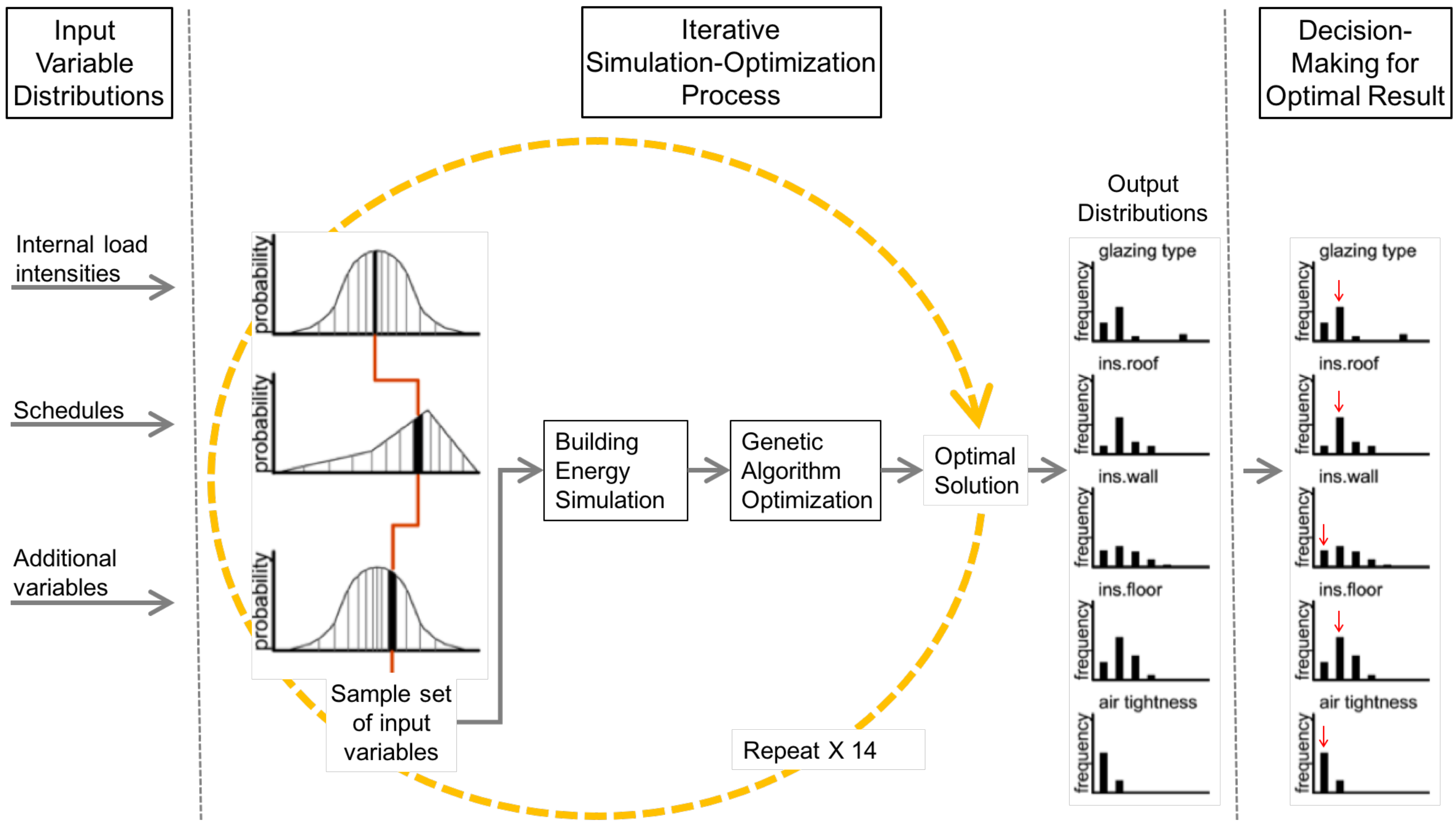

Figure 5.1 Work flow diagram of the simulation-based building optimization process

5.2 Probability Distribution of Input Variables

Internal heat gains, or internal loads, in a space have three major sources: people, lighting, and electric equipment. The amount of internal heat gains depends greatly on the actual use of the space and occupants' behavior [13]. Especially in the residential building, residents' behavior patterns are uncertain and very difficult to predict because they are affected by many factors such as lifestyle, socio-demographic characteristics, and environmental awareness. Every household has its own lifestyle and energy use behaviors as well as different type, size, and age of appliances. It is also difficult to find a clear pattern in schedules of occupancy and lighting in homes. The power consumption pattern of household appliances is also more difficult to estimate compared to that of office appliances that have relatively clearer pattern of usage in accordance with the work schedule. Therefore, if deterministic values are used for these parameters in building energy simulation, it may result in a significant difference from the reality [82]. This research instead takes a stochastic approach by using probability distributions as input variables. Probability distributions are generated for each input variable. A relatively large number of 14 samples has been chosen from each distribution to test the influence of the occupant behavior on the optimization process. Internal load intensity of each space is combined with a room specific schedule of occupancy, lighting, and appliance use to define internal heat gains that are used in building energy simulation. Some additional factors including the occupant behavior of thermostat setting for heating and cooling are considered.

5.2.1 Internal load intensities

Internal load intensities refer to the heat gains in a space from people, electric light, and appliances. Occupancy density, lighting power density, and power consumption of appliances are used for internal load intensities in this study.

5.2.1.1 Occupancy density

This research assumes four-person occupancy. Instead of having a fixed number of four occupants, a distribution of occupancy density (that is made of 14 samples) for each space is created to employ the stochastic approach and to include uncertainty in occupancy density. In other words, it is understandable that even if a family of four lives in a house, the house does not have four-person occupancy all the time. Table 5.1 shows the occupancy density distribution for each space.

Table 5.1 Distribution of occupancy density for each room

Unit: persons

Room	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
Living room	2.8	3.1	3.4	3.5	3.6	3.8	3.9	4.0	4.0	4.1	4.2	4.6	4.8	5.1
Kitchen	0.7	0.8	0.8	0.9	1.0	1.0	1.0	1.0	1.0	1.0	1.1	1.1	1.2	1.3
Dining room	2.8	3.1	3.4	3.5	3.6	3.8	3.9	4.0	4.0	4.1	4.2	4.6	4.8	5.1
Circulation	0.7	0.8	0.8	0.9	1.0	1.0	1.0	1.0	1.0	1.0	1.1	1.1	1.2	1.3
Bedroom 1	0.7	0.8	0.8	0.9	1.0	1.0	1.0	1.0	1.0	1.0	1.1	1.1	1.2	1.3
Bedroom 2	0.7	0.8	0.8	0.9	1.0	1.0	1.0	1.0	1.0	1.0	1.1	1.1	1.2	1.3
Bathroom	1.4	1.6	1.7	1.9	2.0	2.0	2.0	2.0	2.1	2.1	2.2	2.3	2.4	2.6

5.2.1.2 Lighting power density

The internal heat gains from artificial lighting include three types of lamps: incandescent, fluorescent and LED lamps. The average number of lamps in a house is 51 lamps, including 32 incandescent, 2 halogen, 12 compact fluorescent, 5 linear fluorescent, and 0 LED lamps. The information is obtained from the Buildings Energy Data Book [2]. The average number of LED lamps in a residential building is 0 in the reference, but it is expected that the current situation may largely differ, since the reference cites data from 2011 and the use of LED lamps since then has been spreading quickly in residential buildings. Hence, in this research, LED lamps are considered instead of halogen lamps that are not widely used in residential buildings today. Table 5.2 has information of the average number of lamps and lamp wattage of each type of lamp in the residential building. Table 5.3 shows the lighting power density distribution for rooms.

Table 5.2 Lamp type, wattage, and number of lamps in the residential building

Lamp type	Number of lamps	Lamp wattage (W)
Incandescent	32	56
Halogen	2	65
Compact fluorescent	12	16
Linear fluorescent	5	24
LED	0	11

Table 5.3 Distribution of lighting power density for artificial lighting

Unit: W/m^2

	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
All rooms	2.0	6.0	10.0	14.0	14.3	14.6	14.9	15.2	15.5	15.8	16.1	16.4	16.7	18.5

5.2.1.3 Household appliances

Five major household electric appliances are considered in this study: television, personal computer, monitor, stove, and refrigerator. Types of each appliance that are used in the residential building are investigated for their power consumption and installation rates. Then, distributions of heat gains from appliances in each space are created with 14 samples.

Television (TV)

According to the U.S. Energy Information Administration [3], the most common number of TVs in U.S. households is two. Table 5.4 shows the number of TVs in the total U.S. homes and in detached single-family homes, respectively. 33% of the total U.S. homes have two TVs as do almost 30% of detached single-family homes. Approximately 44% of the total U.S. homes have three or more TVs while more than half (54.1%) of detached single-family homes have three or more TVs. The 2011 Buildings Energy Data Book points out that a typical single-family home most likely has three color TVs [2].

Table 5.4 The number of televisions in U.S. homes [3]

Number of TVs	Total U.S.		Detached Single-Family	
	Millions	%	Millions	%
0	1.5	1.3	0.5	0.7
1	24.2	21.3	11.0	15.3
2	37.5	33.0	21.4	29.8
3	26.6	23.4	18.4	25.6
4	14.2	12.5	11.6	16.2
5 or more	9.7	8.5	8.8	12.3
Total	113.6	100.0	71.8	100.0

Traditional standard tube televisions are still the most popular type of TV in U.S. homes; 44.2% of the total U.S. homes have one or more TVs of this type. LCD TVs follow close behind, as 40.5% of the total U.S. homes have at least one LCD TV. On the other hand, the most popular display type of TV in U.S. detached single-family houses is LCD, and the standard tube is the second most popular display type. Table 5.5 summarizes sizes and types of TVs in U.S. homes. More frequently used TVs tend to be bigger and have newer technology of display. The amount of energy consumption of a television is defined by which display technology it has, how big its screen is, and how long it is used during the day. It is easily predictable that a TV with a larger screen draws more power than smaller ones in the same display technology group. It is also evident that a TV consumes more electricity if it is used longer in an active mode. As a result, a larger TV in a household generally uses more energy [141].

There are a lot of data sources that have different categorizations and information about power consumption of TVs. For example, Roth and McKenney group TVs into analog and digital televisions (DTVs). Analog TVs are then categorized into six groups according to their usage frequency: primary, second, third, fourth, fifth, and sixth. DTVs are classified into four subcategories by display type: digital direct view CRT, direct view LCD, plasma, and digital projection. DTVs in each display type are again subcategorized by the screen size. Finally, the weighted average power draw for each display type is calculated based on the power density models developed by the researchers, the estimated installed base, and the usage [141].

Table 5.5 Type and size of televisions in U.S. homes [3]

		Total U.S.		Detached Single-Family	
		Millions	%	Millions	%
Total homes		113.6	100	71.8	100
Most-Used Television					
Display Size	Less than 21”	12.5	11.0	6.4	8.9
	21” to 36”	53.6	47.2	32.0	44.6
	37” or More	46.0	40.5	32.9	45.8
	No TVs	1.5	1.3	0.5	0.7
Display Type	Standard Tube	50.2	44.2	28.9	40.3
	LCD	46.0	40.5	31.0	43.2
	Plasma	9.7	8.5	6.7	9.3
	Projection	5.0	4.4	3.9	5.4
	LED	1.2	1.1	0.9	1.3
	No TVs	1.5	1.3	0.5	0.7
Second Most-Used Television					
Display Size	Less than 21”	32.5	28.6	20.5	28.6
	21” to 36”	43.8	38.6	30.8	43.0
	37” or More	11.6	10.2	8.9	12.4
	No TVs	25.7	22.6	11.5	16.0
Display Type	Standard Tube	56.9	50.1	37.2	51.8
	LCD	25.4	22.4	18.9	26.3
	Plasma	3.8	3.3	2.7	3.8
	Projection	1.4	1.2	1.2	1.7
	LED	0.4	0.4	0.3	0.4
	No TVs	25.7	22.6	11.5	16.0
Third Most-Used Television					
Display Size	Less than 21”	25.0	22.0	18.8	26.2
	21” to 36”	20.5	18.0	15.9	22.1
	37” or More	4.9	4.3	4.1	5.7
	Less than 3 TVs	63.2	55.6	33.0	46.0
Display Type	Standard Tube	35.8	31.5	26.9	37.5
	LCD	11.9	10.5	9.6	13.4
	Plasma	1.5	1.3	1.2	1.7
	Projection	1.0	0.9	0.9	1.3
	LED	0.3	0.3	0.2	0.3
	Less than 3 TVs	63.2	55.6	33.0	46.0

In their report, Roth and McKenney introduce another study on the power consumption of TVs, which measures power draw of 370 analog TVs that were manufactured prior to 1999 [142]. Although it is presumed in their research that the power draw of analog standard tube TVs has not changed noticeably since the mid 1990s, it is reasonable to consider that the power draw might have been reduced since then, due to more advanced technology and stricter energy efficiency codes for electric appliances. For that reason, the current study uses the weighted average power draw of DTVs calculated by Roth and McKenney [141] instead of the older measured data [142].

In addition to Roth and McKenney's four subcategories of DTVs (i.e. digital direct view CRT, direct view LCD, plasma, digital projection) [141], EIA has one more display type of household TVs; that is LED [3], which is a relatively new technology. Among various sources of TV power consumption data, Roth and McKenney's power draw[5] [141] and EIA's installation rate data of display types [3] are chosen to be used in this research. The two studies have a strong basis for their data as well as they are comparatively recent and therefore considered to demonstrate more up-to-date technology and market situations.

The television is a quickly advancing technology, and newer TV technologies have been rapidly penetrating into our homes. As a result, there could be a big change in the household TV market even within just a couple of years. There is only

[5] LED TVs are estimated to be 25% more power efficient than LCD TVs on average.

a three-year difference between the two chosen data sets.[6] Nevertheless, EIA incorporates the LED technology in the display type [3] while Roth and McKenney do not have it in their subcategories [141]. The LED TV is a type of LCD TV that uses light-emitting diodes as a light source; in other words, an LED TV is actually an LED-backlit LCD TV that still uses an LCD panel, and this is why it is often called LED LCD. The categorization of display technologies is important because a TV's power consumption per inch of its screen largely depends on which technology it uses to produce an image. LEDs are generally known to be 20-30% more energy efficient than LCDs. Future categorizations would likely include the OLED (organic light-emitting diode) display that can produce bright and vivid images with less power.

The screen size of a TV also has a great impact on its power consumption. Roth and McKenney maintain that only 9% of DTVs are LCD, and only a small portion of LCD TVs have large screens [141]. This claim, however, seems quite different from the current situation. According to EIA, 40.5% of the total U.S. detached single-family homes have at least one LCD TV [3]. Though EIA's survey data do not provide the household installation rate of screen sizes for LCD TVs, larger screens (37 inches or more) have deeply penetrated overall U.S homes (46 %). It could be said that larger screens currently make a large portion of the LCD TV market.

On the other hand, analog TVs have entered a different situation. Although both the number of U.S. households and the number of televisions per household

[6] Residential Energy Consumption Survey (RECS) by EIA was conducted in 2009 [3], and the study on consumer electronics energy consumption by Roth and McKenney was conducted in 2006 [141].

continue to grow, the number of analog TVs has likely already reached its peak as digital TVs (DTVs) have become increasingly popular. Moreover, broadcasting switched their signals from analog to digital in 2009, and all TVs sold in and after March 2007 must have a DTV tuner.

Personal computer (PC)

A typical single-family home has two computers [2]. However, another survey reports that U.S. homes most commonly have one computer [3]; 41.3% of the total U.S. homes have one computer, 21.4% have two computers, and 13.3% have three or more computers. Among detached single-family homes, 40.4% have one, 24.2% have two, and 17.0% have three or more computers. Table 5.6 summarizes the number of computers in U.S homes [3].

Table 5.6 The number of computers in U.S. homes [3]

Number of computers	Total U.S.		Detached Single-Family	
	Millions	%	Millions	%
0	27.4	24.1	13.3	18.5
1	46.9	41.2	29.0	40.4
2	24.3	21.4	17.4	24.2
3	9.5	8.4	7.5	10.4
4	3.6	3.2	3.0	4.2
5 or more	2.0	1.8	1.7	2.4
Total	113.6	100.0	71.8	100.0

The most-used computer in homes is a desktop PC while the second most-used computer is a laptop PC [3]. Table 5.7 shows power consumption of desktop and laptop computers at their different modes [2]. The operating modes of PCs can be categorized into three groups: active, idle, and off. The active mode refers to when a computer is either being actively used or not being actively used but still remains on before entering into the sleep, or power saving, mode. When a computer is turned off, but if it's still plugged in, it is the off mode [141].

Table 5.7 Power draw and usage of computers [2]

	Power Draw (W)			Annual Usage (hours/year)		
	Active	Idle	Off	Active	Idle	Off
Desktop	75	4	2	2,990 (34%)	330 (4%)	5,440 (62%)
Notebook	25	2	2	2,368 (27%)	935 (11%)	5,457 (62%)

Monitor

The monitor in this study refers to the stand-alone computer monitor that is used with desktop PCs. There are 90 million desktop PCs in U.S households, which stands for 90 million monitors in U.S. households, assuming that one desktop PC yields one stand-alone monitor. Though either a PC could have multiple monitors or a laptop could be connected to one or more monitors, this was regarded not to have much influence on the estimated installed base [141].

The data shown in Figure 5.2 demonstrates power consumption of monitors in different types and sizes in the active mode. Monitors use most power while they are in active among the three operating modes (i.e. active, idle, and off). It is noteworthy that there is no noticeable difference in power consumed during the idle and off modes between sizes and types of monitors.

Monitors are grouped into 4 categories according to their type and size: 15" LCD monitors, 17" LCD monitors, 19" LCD monitors, and 17" CRT monitors. The average power consumed by a 15" LCD monitor was 20W, and 15% of U.S. households have this type and size of monitors. A 17" LCD monitor draws 31W of power on average, and it is installed in 35% of homes in the U.S. The average power for 19" LCD monitors was 35W, and their installation rate was 10%. Lastly, 17" CRT monitors averagely use 61W, and their installation rate was 40% among U.S. homes [141]. Overall, LCD monitors use less power than CRT monitors regardless of the size.

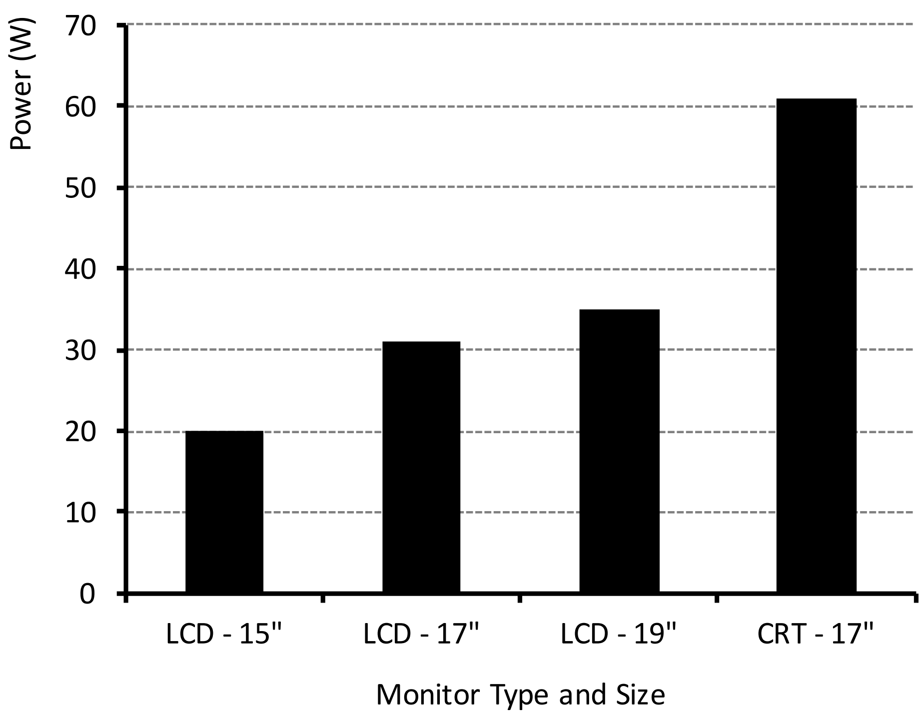

Figure 5.2 Types and sizes of monitors and power consumption

Stove

The most popular cooking appliance in U.S. homes is the stove that consists of an oven and a cooktop. Other options include separate cooktops, separate wall ovens, and built-in/stove-top grills. 86.8% of U.S. detached single-family households have at least one stove. Among the homes that have one or more stoves, 60% use electricity as the stove fuel, 34.6% natural gas, and only 5.4% use propane/LPG [3]. In the same manner, the 2011 Buildings Energy Data Book [2] indicates that a typical single-family home has an electric range/oven. In this study, the electric stove is therefore used as a representative cooking appliance in the kitchen of the single-family house.

The stove top power varies depending on the size of burners and temperature setting (i.e. high, medium, or low), ranging generally between 1,000W and 3,000W. A stove top does not always use its maximum rated power once it reaches a target temperature. Thus, it is imprecise to use a fixed value for the power consumption of a stove. Instead, it is estimated that a stove uses 1,500W per hour on medium to high heat [143]. Since there is no available information about types of stoves and their installation rate in homes, the frequency of stove usage (i.e. three times a day, twice a day, once a day, once to a few times a week, and less than once a week) is used to create the probability distribution.

It is assumed that a stove is used for 30 minutes per each meal preparation. This assumption is made based on a published study that investigates dinner preparation in 32 families by using direct observation. The average total dinner preparation time is 52 minutes[7] [144]. Not only because this total preparation time would not fully integrate stove usage, but also because dinner preparation time in general tends to be longer than other meals, 30 minutes of average meal preparation time is assumed in the current study. This average meal preparation time is combined with the frequency of hot meal cooking [3] to generate probability distributions of stove energy consumption in detached single-family homes in the U.S. (Table 5.8). Energy consumption per day by stove is calculated as:

$$1500\ W \times 0.5\ h \times (meal\ preparation\ frequency\ per\ day)$$
$$= energy\ consumption\ of\ the\ stove\ each\ day$$

Table 5.8 Stove power use and household installation ratio

Frequency of hot meals cooked[8]	Energy per day (Wh)	Probability (%)
3 or more times a day	2,250	7.1
2 times a day	1,500	24.2
Once a day	750	39.1
Once to a few times a week	296	25.3
Less than once a week	0	4.3

Refrigerator

Refrigerators have a distinctive electricity consumption pattern from other household appliances. Unlike other household appliances that are turned on and

[7] The average hands-on time was 34 minutes.

[8] The hot meal cooking frequency is regrouped into the five categories shown in Table 5.8. The original categorization in RECS (Residential Energy Consumption Survey) has seven categories: (1) 3 or more times a day, (2) 2 times a day, (3) once a day, (4) a few times each week, (5) about once a week, (6) less than once a week, and (7) no hot meals cooked [3].

actively draw electric power only when they are being used, refrigerators are always turned on and constantly use electricity. However, they may not always use their peak power. Because of this unique pattern of power usage, it is neither appropriate to directly use their power consumption information nor the information is available. In this current study, refrigerators are grouped into five categories by their size: (1) less than 7 cubic feet, (2) 7-14 cubic feet, (3) 15-18 cubic feet, (4) 19-22 cubic feet, and (5) 23 cubic feet and larger [3]. Then, the average annual energy use (kWh/year) is calculated for each group [145][9]. Average power (W) for each group of refrigerators is calculated based on their annual energy use.

Older refrigerators tend to consume more energy [137]. In the database of refrigerator energy efficiency that is used in the current study [145], the oldest refrigerators have very low energy efficiency that acts as outliers in the dataset. In order to mitigate biased influence of outliers (i.e. unduly low energy efficiency from very old refrigerators), data prior to 1994 are removed from the database. In fact, only 4.2% of detached single-family households use a 20-year or older refrigerator as their most-used refrigerator [3].

[9] The California Energy Commission website (www.energy.ca.gov) has historical appliances data files. 'Non-commercial refrigerators' and 'non-commercial refrigerator-freezers' data under the 'refrigeration' directory are used in this study.

Table 5.9 Refrigerator power use and household installation ratio [3,145]

Total Volume (Cu. Ft.)			< 7	7-14	15-18	19-22	> 23
Annual Energy Use (kWh/yr)	Refrigerators		335.5	373.5	417.0	482.7	543.4
	Refrigerator-Freezers	Bottom Freezer w/ Ice Thru Door	N/A	N/A	N/A	570.1	553.5
		Bottom Freezer w/o Ice Thru Door	499.4	581.5	1,439.2	755.1	522.7
		Internal Freezer	395.3	588.4	1,150.3	1,480.5	1,862.0
		Side-by-Side w/ Ice Thru Door	N/A	N/A	1,342.6	941.5	1,027.9
		Side-by-Side w/o Ice Thru Door	531.9	845.4	1,527.1	1,288.7	1,233.2
		Top Freezer w/ Ice Thru Door	N/A	N/A	955.5	978.2	1,085.3
		Top Freezer w/o Ice Thru Door	438.8	812.2	869.7	969.5	878.3
		Kitchen Units	472.8	504.2	N/A	N/A	N/A
Average Annual Energy Use (kWh/yr)			445.6	617.5	1,100.2	933.3	963.3
Average Power Draw (W)			50.9	70.5	125.6	106.5	110.0
Installed Base in Detached Single-Family Homes		Million	0.2	1.7	26.5	35.6	7.7
		%	0.3	2.4	37.0	49.7	10.7

Table 5.10 Age of most-used refrigerator in U.S. homes

Age	Total U.S.		Detached Single-Family	
	Millions	%	Millions	%
Less than 2 years	14.0	12.3	9.2	12.8
2 to 4 years	26.1	23.0	15.9	22.2
5 to 9 years	39.9	35.1	25.0	34.9
10 to 14 years	21.1	18.6	13.7	19.1
15 to 19 years	7.1	6.2	4.8	6.7
20 years or more	5.3	4.7	3.0	4.2
Do not use a refrigerator	0.2	0.2	0.1	0.1

Table 5.11 summarizes the power consumption data of household electric appliances and their installation or usage rates for the subcategories. This is used to create the probability distributions of household appliances as input variables for the simulation-optimization process.

Table 5.11 Input variable settings of household appliances with probability distribution of power

TV	Display type	LCD	Standard tube	Plasma	Projection	LED
	Probability (%)	43.3	40.5	9.4	5.5	1.3
	Power (W)	72	92	340	200	54
PC	Operating mode	Active		Idle		Off
	Probability (%)	34		3		62
	Power (W)	75		4		2
Monitor	Type & size	LCD 15”	LCD 17”	LCD 19”		CRT 17”
	Probability (%)	15	35	10		40
	Power (W)	20	31	35		61
Stove	Usage	3 times a day	Twice a day	Once a day	Once to a few times a week	Less than once a week
	Probability (%)	7.1	24.2	39.1	25.3	4.3
	Daily energy (Wh)	2250	1500	750	296	0
Refrigerator	Size (cu. ft.)	<7	7 to 14	15 to 18	19 to 22	>23
	Probability (%)	0.3	2.4	37.0	49.7	10.7
	Power (W)	51	70	126	107	110

The distribution of the total internal heat gains from people, lighting, and appliances in each space are listed in Table 5.12. The samples in the distribution are combined with room specific schedules to define hourly internal heat gains in each space.

Table 5.12 Maximal internal heat gains from appliances (W/m^2)

	Living room	Kitchen	Dining room	Circulation	Bedroom 1	Bedroom 2	Bathroom
Sample 1	75.4	353.6	0	0	20	20	0
Sample 2	82	486.2	0	0	20	20	0
Sample 3	88.6	581.4	0	0	25	25	0
Sample 4	95.2	656.2	0	0	27	27	0
Sample 5	101.8	725.9	0	0	29	29	0
Sample 6	108	789	0	0	31	31	0
Sample 7	115	850	0	0	33	33	0
Sample 8	115.8	850	0	0	35	35	0
Sample 9	116.6	911.2	0	0	58	58	0
Sample 10	117.4	974.1	0	0	59	59	0
Sample 11	118.2	1043.8	0	0	60	60	0
Sample 12	119	1118.6	0	0	61	61	0
Sample 13	120.6	1213.8	0	0	62	62	0
Sample 14	193	1346.4	0	0	63	63	0

5.2.2 Room specific schedules

The residential building energy use is largely dependent on residents' behaviors, but it is impossible to predict the behavior pattern accurately in advance. It is even not plausible to know the precise schedule of internal loads because our everyday life is affected by too many factors and changes frequently and unexpectedly. It is therefore reasonable and necessary to include uncertainty into occupancy, lighting, and appliance usage schedules. The average schedules for the internal loads are illustrated in Figures A.1 and A.2 in Appendix A. The hourly internal load schedules are listed in Tables B.1 through B.21 in Appendix B. These give an overview to the schedules as input variables with uncertainty used for the Latin hypercube sampling in the iterative simulation-optimization process. The internal load schedules are assumed to have a normal distribution; the minimal and maximal values are 20% higher or lower than the mean, respectively.

5.2.3 Additional variables

A few additional variables are considered to include uncertainty from other possible sources. Uncertainty in thermostat setpoint temperatures for heating and cooling is taken into consideration since they have a great impact on heating and cooling energy use [146]. Uncertainty in the calculation process of a simulation tool is also considered by giving variations to heating and cooling energy demands. Life cycle cost is selected as the objective function of the optimization problem in this study, and thus uncertainties in the initial and operation costs are also taken into account. A normal distribution of 20% difference from the mean is given to these three variables. Since all needed information is not always available for the probability distribution of input variables, it is typically assumed that most variables have a Gaussian or uniform distributions [88,124,131]. Tables 5.13 through 5.15 show the distributions for thermostat setpoint temperature, heating and cooling energy demands, and costs.

Table 5.13 Thermostat setpoint temperatures for heating and cooling (°C)

	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
Heating	15	17	17	19	19	19	19	19	20	20	20	22	22	24
Cooling	20	20	21	21	22	22	23	23	23	24	24	24	25	26

Table 5.14 Simulation energy demands for heating and cooling (%)

	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
Heating	0.78	0.83	0.88	0.91	0.94	0.97	1.00	1.00	1.03	1.05	1.08	1.12	1.16	1.22
Cooling	0.78	0.83	0.88	0.91	0.94	0.97	1.00	1.00	1.03	1.05	1.08	1.12	1.16	1.22

Table 5.15 Initial and operation costs (%)

	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
Initial	0.78	0.83	0.88	0.91	0.94	0.97	1.00	1.00	1.03	1.05	1.08	1.12	1.16	1.22
Operation	0.78	0.83	0.88	0.91	0.94	0.97	1.00	1.00	1.03	1.05	1.08	1.12	1.16	1.22

5.3 Iterative Simulation-Optimization Process

In this iterative simulation-optimization process, the genetic algorithm (GA) that is combined with the Latin hypercube sampling method and the thermal simulation program is run repeatedly to investigate the results of a building optimization problem with varying input variables of internal heat gains.

5.3.1 Latin hypercube sampling

As discussed in ‘4.3 Scope of the Thesis,’ it is more realistic to use a stochastic approach for a building optimization problem, and the Monte Carlo method is the most commonly used non-structured method for uncertainty analysis. Monte Carlo allows for the combination of different potential settings of input variables based on random sampling. However, a random sampling method has the major disadvantage of requiring a large number of simulation runs to provide reliable results. A more effective way is to use the Monte Carlo technique in combination with a sampling algorithm to reduce the needed number of optimization runs.

This study implements the Latin hypercube sampling (LHS) method to define the input variables of interest while integrating probability distributions of input variables. This is how the current study takes into account uncertainties by allowing variation in input variables and explores the effect of integrating uncertainties on a building optimization problem. The LHS method is a type of stratified sampling; the domain of each input variable is divided into the same number of disjoint intervals with equal probability to ensure that each section has the same chance of being chosen. By doing so, variable settings with a small probability (extreme cases) are guaranteed to be taken into account for their influence on the optimization result. A sample from each interval of each variable is chosen once per sampling to make sure variations in output distributions of optimization results. Thus, the number of samples (i.e. 14 samples) generated by each sampling run is defined by the number of intervals (i.e. 14 intervals).

The main advantage of the LHS method is that it requires a reduced number of calculations to obtain output distributions while covering the entire distribution area of a variable. That is to say, the LHS improves sampling efficiency and convergence, and therefore is superior to other sampling methods that generate randomly distributed sequences. [88,122,125–127,147]. The LHS method has been successfully applied to solve complex, nonlinear problems and has proven its suitability in building simulation [148]. The major use of the LHS method is for uncertainty propagation in sensitivity analysis [125,149,150]. It is also used for the clarification of uncertainties in simulation results [119,130,134,151]. However, none of these studies employ uncertainty analysis into simulation-based building optimization. This study uses the LHS method to investigate the influence of user behavior-related input variables on the building optimization results.

5.3.2 Simulation-optimization

The input variables generated by the LHS method are used for building energy simulation using EnergyPlus that is combined with the genetic algorithm (GA) optimization. The LHS system and the GA are developed and programmed in C++.

5.3.2.1 Model and locations

The input variable uncertainties associated with the user behavior are considered in this study for a typical residential building in the U.S. Three major cities (Chicago, IL; Madison, WI; and Washington, D.C.) are used to test the proposed method of the LHS combined simulation-based optimization.

Typical U.S. single-family home

It is necessary to define a model home that is used in this research. The 2011 Buildings Energy Data Book [2] provides an accurate and up-to-date statistical compendium for building-related data in the overall building sector, the residential sector, the commercial sector, the federal sector, building envelope/ equipment, energy supply, energy codes/standards/laws, water data, and market transformation. The second chapter of the 2011 Buildings Energy Data Book focuses on the residential sector including its energy-related data, characteristics of average households, construction, and housing market. In this chapter, characteristics of a typical single-family home are specified, which are used in the model home in this research. Figure 5.3 shows an isometric sketch of the test building, and Table 5.16 describes the characteristics of the typical U.S. single-family home.

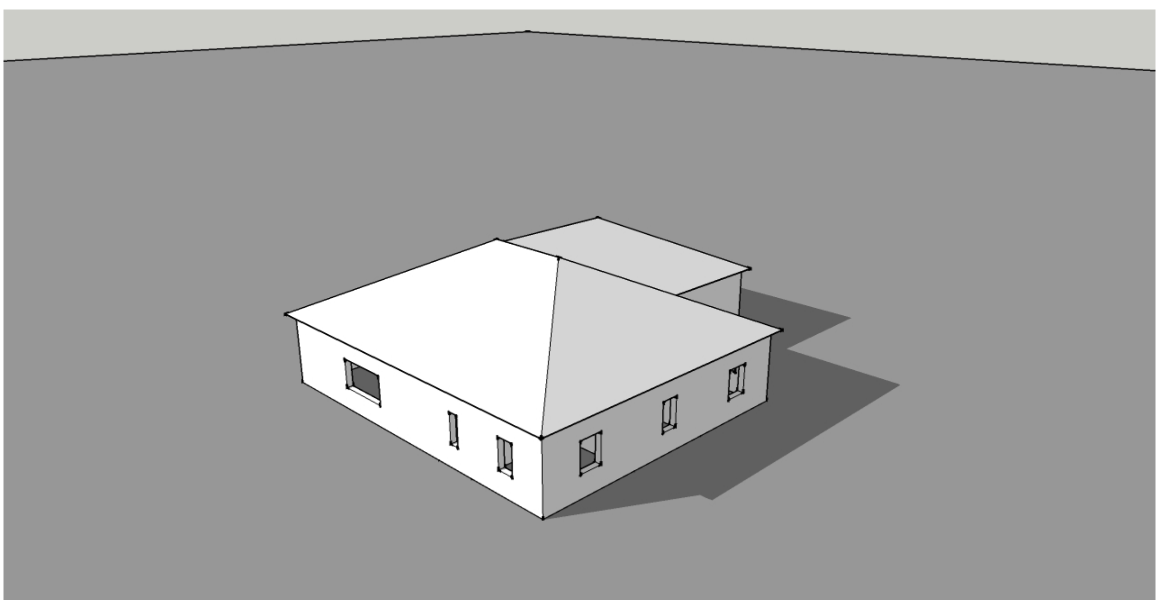

Figure 5.3 Isometric sketch of the test single-family house

Table 5.16 Structural characteristics of a typical single-family home [2]

Year Built		mid 1970s
Floorspace	Heated Floorspace	1,934 ft^2 (180 m^2)
	Cooled Floorspace	1,495 ft^2 (139 m^2)
	Garage	2-Car
Stories		1
Foundation		Concrete Slab
Rooms	Bedrooms	3
	Other Rooms	3
Bathrooms	Full Bathroom	2
	Half Bathroom	0
Windows	Area	222 ft^2 (20.6 m^2)
	Number	15
	Type	Double-Pane
Insulation		Well or Adequate

Based on the structural characteristics of an average single-family home described in Table 5.16, a test house for building energy simulations that represents a typical U.S. home is modeled using the DesignBuilder software. The modeled residential building has 1,934 ft^2 (180 m^2) of heated area. The test building is a one-story three-bedroom single-family house and has a master suite (master bedroom and a master bathroom) with two additional bedrooms. It is assumed to be occupied by four people. It also has one separate full bathroom, a kitchen with an adjacent dining room, a living room, and an entry (i.e. circulation area). The average window area is 222 ft^2 (20.6 m^2) consisting of 15 double-pane windows.

5.3.2.2 Genetic algorithm optimization

In this research, the genetic algorithm (GA) optimization that is coupled with the building simulation is used to find the optimal solution. An optimization algorithm is run for each combination of input variable samples that is generated by the LHS methods. As 14 sample sets are generated by each sampling run, 14 optimization runs are carried out, and 14 discrete optimization results are produced for each location. For a higher accuracy for the statistical analysis, two sampling runs generating 28 sample sets in total are conducted for three locations (Chicago, IL; Madison, WI; and Washington, D.C.). Each generation of the GA involves a population of 40. An elitism criterion is used for a fast emerging process. The results of the optimization provide (1) the combination of the optimal parameter settings for the input variables used for the optimization run and (2) the normalized life cycle cost as the objective function of the optimization process. It is assumed the optimal solution is reached if the same result (within 0.5% of difference) is found for three consecutive iterations, after at least ten generations.

Because of the design of the LHS method, there is the risk that the sample sets of input variables may not cover all plausible cases of occupant behaviors. In other words, because the LHS method guarantees that the entire probability distribution of each input variable is covered, the generated sample sets may not include some extreme cases. For example, the occupant behavior of a family whose members are highly concerned about their energy use and have high environmental awareness may largely differ from the average occupant behavior. On the other hand, a household of a big family may also have a very different energy use pattern from typical occupants. In order to take into account these unusual but plausible cases of occupant behavior, biased optimization runs are conducted using biased input variables reflecting a household of a very high energy demand and a household of a very low energy demand. Only one location (Chicago, IL) is used for the biased optimizations as additional information. High internal heat gain values (i.e. high appliances power consumption, high occupancy density, and long occupation periods) represent the high bias optimization. Low internal heat gain values (i.e. low appliances power consumption, low occupancy density, and short occupation periods) represent the low bias optimization.

5.3.2.3 Optimization parameters

The optimization problem has five parameters: (1) glazing type, (2) wall insulation, (3) roof insulation, (4) floor insulation, and (5) the air change rate of the infiltration (air tightness). Table 5.17 shows the physical properties and estimated investment costs of each parameter setting of the five optimization parameters. The estimated physical properties and investment cost are taken from the U.S. Department of Energy's Building America program [152] and the commercially available R.S. Means software program [153].

Table 5.17 Parameter settings of the optimization problem

Parameter	Parameter setting	Investment cost ($/m^2)	U-value (W/m^{2}K)	SHGC[10]	Light transmittance	ACH[11]
Glazing	1	365	2.20	0.20	0.25	-
	2	344	1.57	0.31	0.62	-
	3	436	1.20	0.31	0.62	-
	4	360	1.66	0.62	0.68	-
	5	365	1.20	0.52	0.58	-
	6	570	0.70	0.51	0.58	-
Wall, roof, floor insulation	1	8.13	0.7	-	-	-
	2	11.5	0.46	-	-	-
	3	14.8	0.37	-	-	-
	4	18.1	0.32	-	-	-
	5	25.7	0.26	-	-	-
	6	29.0	0.19	-	-	-
	7	32.3	0.12	-	-	-
Air tightness	1	4.5	-	-	-	0.25
	2	12.9	-	-	-	0.18
	3	24.8	-	-	-	0.15
	4	31.2	-	-	-	0.12

5.3.2.4 Objective function

This study uses a single-objective genetic algorithm to find the optimal combination of parameter settings for a typical U.S. single-family house. The net present value of the life cycle cost (LCC) is used as the objective function and is calculated by the following equation:

$$LCC = I_{initial} + t\times(Q_{site}\times P\times 1/(1+P)^t)$$

where

$I_{initial}$ = initial investment cost

Q_{site} = site energy demand

[10] Solar heat gain coefficient
[11] Air changes per hour, or air change rate

P = present energy cost

t = calculated life-time period for the LCC

The LCC analysis properly considers money spent today and money spent in the future. The total cost, that is the sum of all relevant costs converted into common, current dollars, is expressed in present dollars to compare each alternative [154]. In this study, the year 2010 is used for the present energy cost. Maintenance cost and residual cost are not included in this study.

The average increase of present energy cost for natural gas is taken from the energy price indices of the National Institute of Standards and Technology [155]. In the U.S., this cost is projected to increase by 1.15% per year for natural gas from 2010 to 2040. The life-time period for this study that is used for the LCC analysis is 30 years.

5.4 Decision-Making for Optimal Result

Booth and Choudhary mention that "identifying the various sources of uncertainty and quantifying the resultant uncertainty in outputs of interest is only part of the problem. In addition, there needs to be a framework that allows DMs[12] to utilize this additional information" (p.298) [87]. This statement emphasizes the need and importance of a decision-making framework that can help in making a robust decision among available alternatives. This research uses the frequency of

[12] Decision makers

recommendations, the test of proportion, and the Hurwicz criterion as evaluation criteria for the robust decision-making.

5.4.1 Frequency of recommendations

The frequency of recommendations for a parameter setting is used as an indicator of the influence of the uncertainty in input variables on the optimization results. If one parameter setting is recommended far more than other parameter settings, this means that the most recommended parameter setting is the optimum, regardless of varying user behavior-related input variables. In other words, it implies a small influence of the occupant behavior on the optimization parameter. This research uses the frequency of recommendations for parameter settings as the first indicator for the robust decision-making from the optimization results. The most recommended parameter setting for an optimization parameter is regarded as the best solution.

5.4.2 Test of proportion

The test of proportion is used to evaluate whether the frequencies of recommendations of two parameter settings have the statistically significant difference. In this study, it is tested whether or not the proportion (P) of the number of recommendations of one parameter setting to the sum of the number of recommendations of that setting and one other setting is over 0.5. For example, when a parameter setting gets 23 recommendations while another setting gets 30 recommendations, the significance level of the proportion of 30 to 53 (i.e. 23+30) from 0.5 is calculated. Therefore, the null and alternative hypotheses are expressed as:

$$H_0: P \leq 0.5$$

$$H_a: P > 0.5$$

The test of proportion calculates the significance level, or p-value, using a general z-test for the observed sample proportion.

$$z = \frac{\hat{P} - P_0}{se(\hat{P})}$$

where

$\hat{P}$ = observed proportion

P_0 = the Null hypothesis (or expected) proportion

$se(\hat{P})$ = the standard error of the expected proportion

$$se(\hat{P}) = \sqrt{\frac{P_0(1 - P_0)}{n}}$$

where

n = sample size

The next step is to determine the p-value using the calculated z-value. Once p-value is determined, it is time to decide between the null (H_0) and alternative (H_a) hypotheses. If p-value $\leq a$, reject the null hypothesis. If p-value $> a$, fail to reject the null hypothesis. When the null hypothesis is rejected by examining the p-value, the test result is said to be statistically significant. The value for a is defined by researchers, but $a = .05$ is the most commonly used value.

If there is a statistically significant difference between the most recommended and the second most recommended parameter setting, the most frequently recommended one is selected as the optimum solution. However, if the test result says there is no statistically significant difference between the two settings, the test of proportion is carried out for the most recommended and the third most recommended parameter settings. This is repeated until a significant difference is found between the most recommended parameter setting and the *n*th recommended parameter setting. This process is illustrated in Figure 5.4. Once the statistical significance of recommended parameter settings is identified, the next step is to apply the Hurwicz decision rule to choose a better solution among settings that do not have statistically significant difference between them.

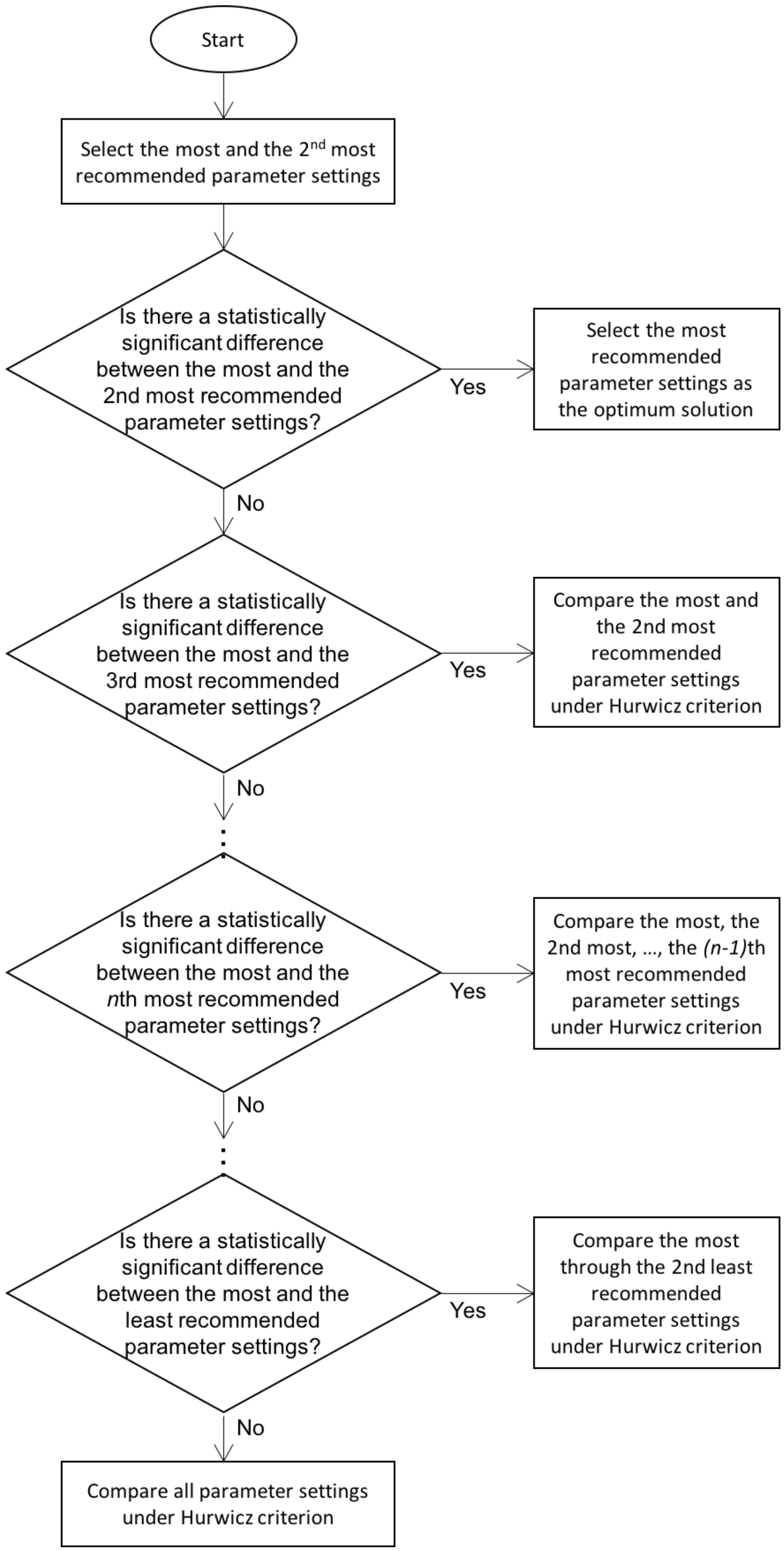

Figure 5.4 Flow of the test of proportion

5.4.3 Decision-making under the Hurwicz criterion

In this research, the Hurwicz decision rule is used as an evaluation criterion for robust decision-making of the parameter settings that are assessed to have no statistically significant difference between them according to the result of the test of proportion. Because the probabilities of states of nature, which are a necessary element for decision rules under risk, are not available, decision–making under risk criteria cannot be used for this study. This is one of the major disadvantages of probabilistic decision rules. Non-probabilistic decision rules (decision-making criteria under uncertainty) are actually widely used in the field of energy and environmental modeling [156]. The Hurwicz criterion is one of the non-probabilistic decision-making rules, and it allows adjustment of a decision maker's personal view between optimistic and pessimistic conditions by modifying the value of the coefficient of optimism, or Hurwicz index, H. If a decision maker is risk-averse, H=0.3 is used. If a decision maker is a risk-seeker, H=0.7 is used. For a decision maker who has a risk-neutral attitude, H=0.5 is used. The flow of application of the Hurwicz criterion is illustrated in Figure 5.5. The Hurwicz criterion is expressed as [8]:

$$X^H(q,H) = (1-H)X(q,s^0) + HX(q,s^1)$$

where

X = objective value of available options

q = available options

s^0 = globally pessimistic scenario

s^1 = globally optimistic scenario

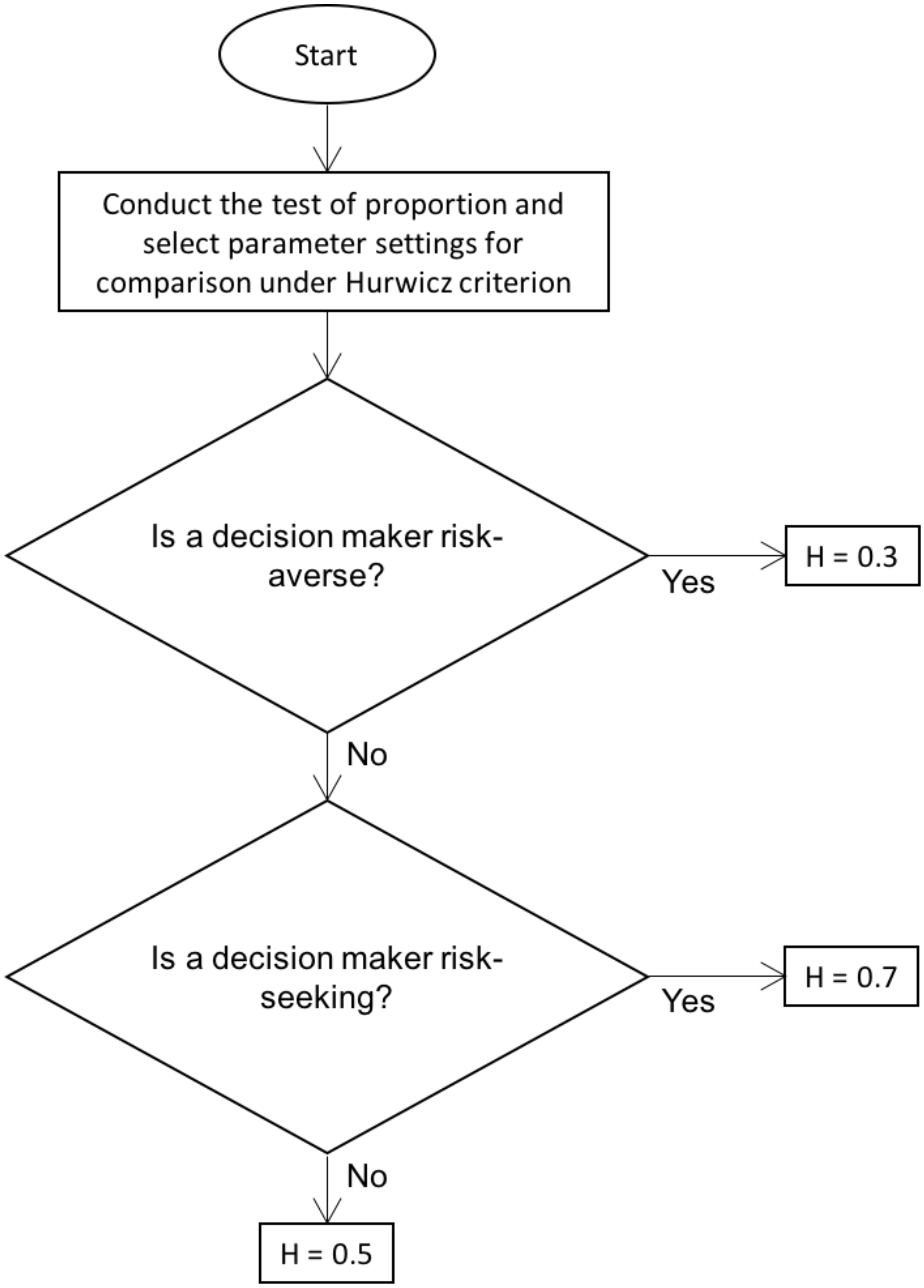

Figure 5.5 Flow of application of the Hurwicz criterion

CHAPTER 6

RESULTS AND ANALYSIS

This chapter describes the results of the simulation-based building optimization process and robust decision-making from the optimization results. First, the results of the life cycle cost of the Latin hypercube sampling runs are shown for each location. Second, the results of the recommended parameter settings are discussed. Third, the results of the biased optimization runs are introduced. Finally, the results of the introduced decision-making framework are presented.

6.1 Life Cycle Cost (LCC)

The results of the LCC give a general overview of the range and distribution of the LCC calculations as the objective function. Figure 6.1 shows the variation of the results of the LCC calculations for all sampling runs for all three locations. One output distribution contains the results from two LHS runs, so each distribution shows 28 optimization results. Hence, each location has results that are generated from 84 optimization runs.

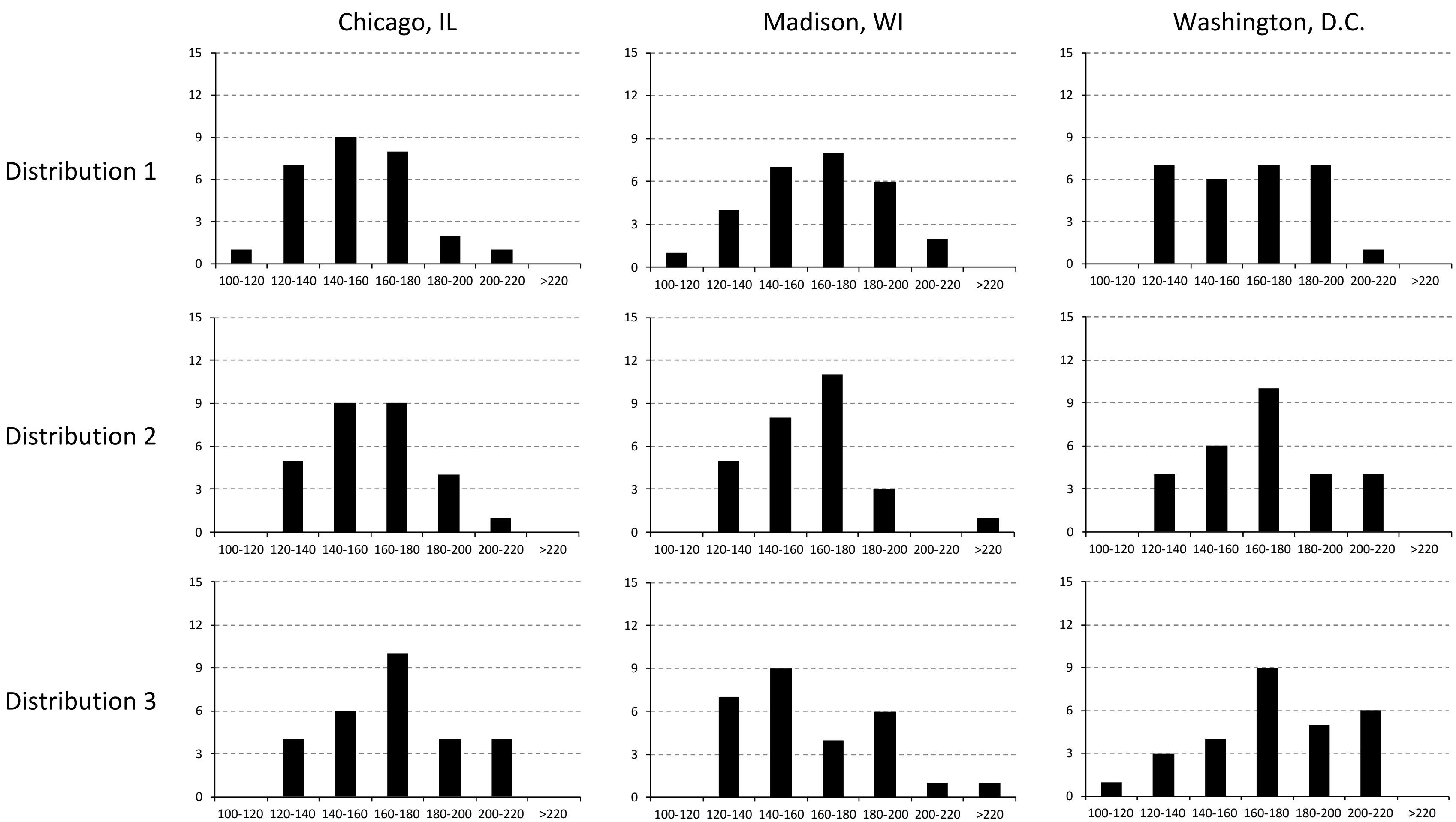

Figure 6.1 Distributions of the life cycle cost by using the LHS method

The different values of the calculated LCC result from varying input variables defined by the LHS. For Chicago, IL, the mean LCC values are \$155.7/m^2, \$160.4/m^2, and \$167.5/m^2, respectively for Distributions 1, 2, and 3. The total mean value of LCC is \$161.2/m^2. The most popular range for the LCC value of each optimization run is between \$160/m^2 and \$180/m^2, and the range between \$140/m^2 and \$160/m^2 follows in a narrow margin. 58.3% of the total LCC calculations fall within the range of \$140/m^2 to \$180/m^2. The entire range of the LCC data is from \$119.2/m^2 to \$213.4/m^2.

For Madison, WI, the mean LCC value of each distribution is \$164.3/m^2, \$161.3/m^2, and \$163.6/m^2, respectively. The total mean value of LCC is \$163.0/m^2. The most popular range for the LCC value of each optimization run is between \$140/m^2 and \$160/m^2, and the range between \$160/m^2 and \$180/m^2 follows with a slight difference. 56.0% of the total LCC calculations fall within the range of \$140/m^2 to \$180/m^2. The entire range of the LCC data is from \$117.2/m^2 to \$249.8/m^2. The overall LCC results of Chicago and Madison are shown to be similar to each other, except the two cases of LCC over \$220/m^2 in Madison. This seems to be derived from the similar climate of the two cities, while Madison has a little colder winter [157].

For Washington, D.C., the mean LCC of the three distributions are, respectively, \$162.9/m^2, \$169.3/m^2, and \$173.3/m^2. The total mean is \$168.5/m^2. The most popular range of LCC is \$160/m^2 and \$180/m^2, and 31% of the total LCC data are included in this range. The entire LCC data range between \$118.9/m^2 and \$218.6/m^2. The LCC results for Washington, D.C. are generally similar to those of the other two cities. Considering the relatively warmer winter of Washington, D.C., the similar results seem to be derived from its warmer summer weather. Summers are hot and humid in Washington, D.C., and the resultant larger cooling energy consumption compared to other two locations might offset the effect of the smaller heating energy consumption. Table 6.1 summarizes the average climate of the three locations [157].

Table 6.1 Average climate of Chicago IL, Madison WI, and Washington D.C. [157]

Unit: °C

	Chicago, IL	Madison, WI	Washington, D.C.
Annual high temp.	13.8	13.2	18.2
Annual low temp.	5.8	2.7	8.1
Average temp.	9.8	7.9	13.2

In most cases shown in Figure 6.1, the distributions of the LCC results of the LHS runs follow the principle of the normal distribution. This is in line with the results of other researcher's published studies [134,148,158]. According to the *law of large numbers*, the tendency towards the normal distribution is more evident with a larger number of samples. The following Figure 6.2 demonstrates the sum of the LCC results of the three distributions for each location shown in Figure 6.1, and therefore, each graph has the total of 84 optimization results. The trend towards the normal distribution is noticeable in all three locations.

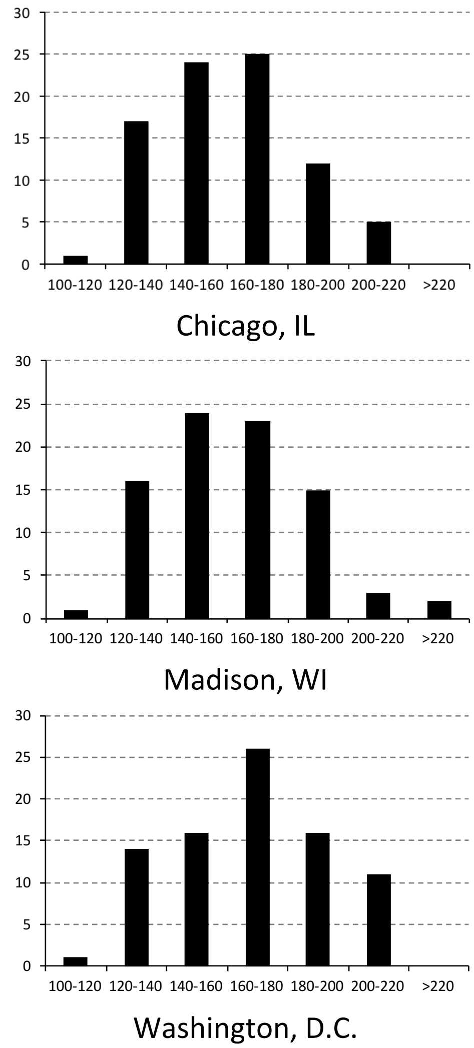

Figure 6.2 The sum of three distributions of the LCC

6.2 Optimization Results for Parameters

Five parameters including glazing type (parameter 1), wall insulation (parameter 2), roof insulation (parameter 3), floor insulation (parameter 4), and air tightness (parameter 5) are used in this study for optimization. Figures 6.3 through 6.5 shows the frequency of recommendations as the optimization result for each parameter and parameter setting for each location. The main purpose of the sampling and optimization runs for Madison, WI and Washington, D.C. is to verify the results for Chicago, IL.

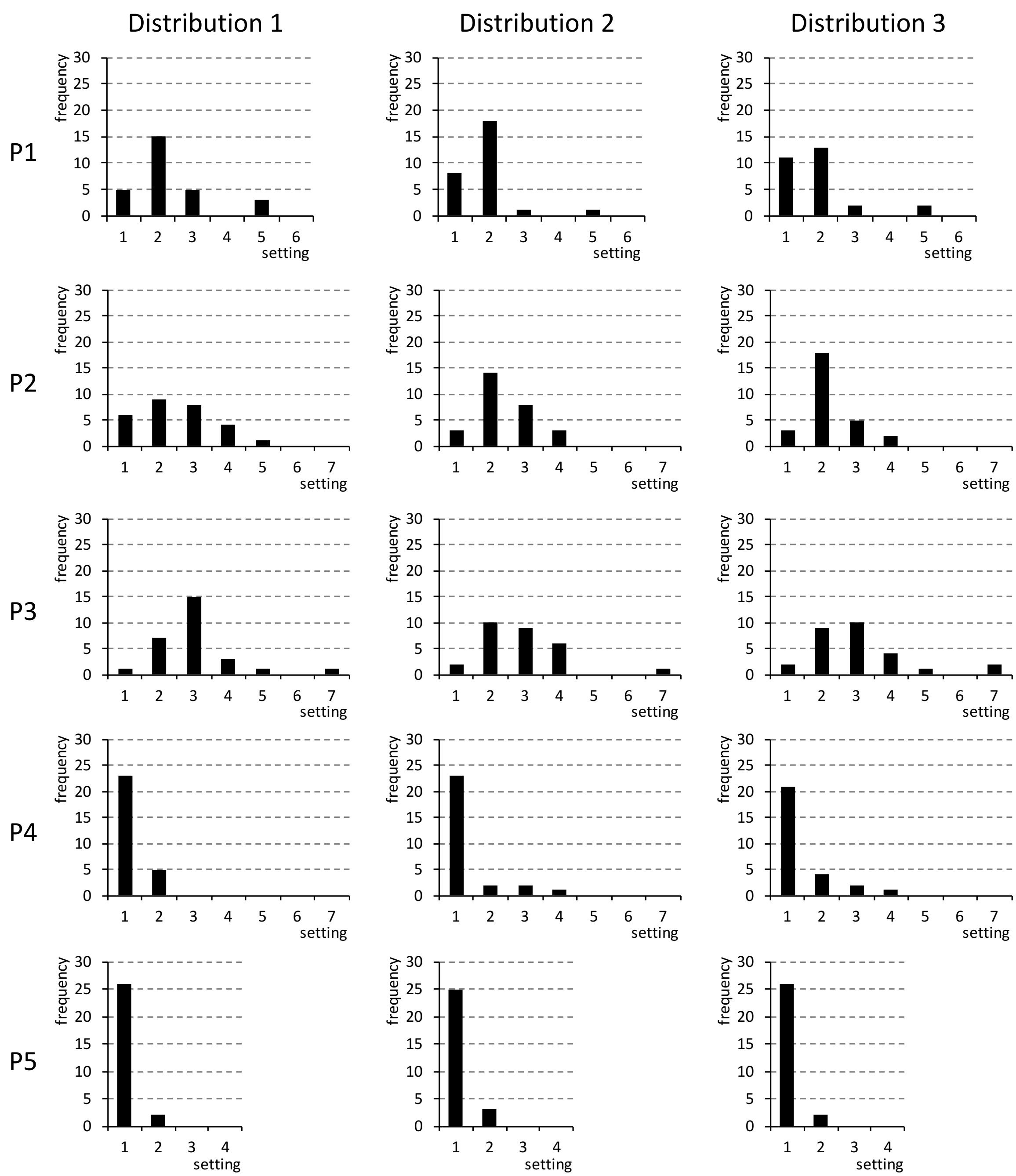

Figure 6.3 Distributions of recommended parameter settings for Chicago, IL

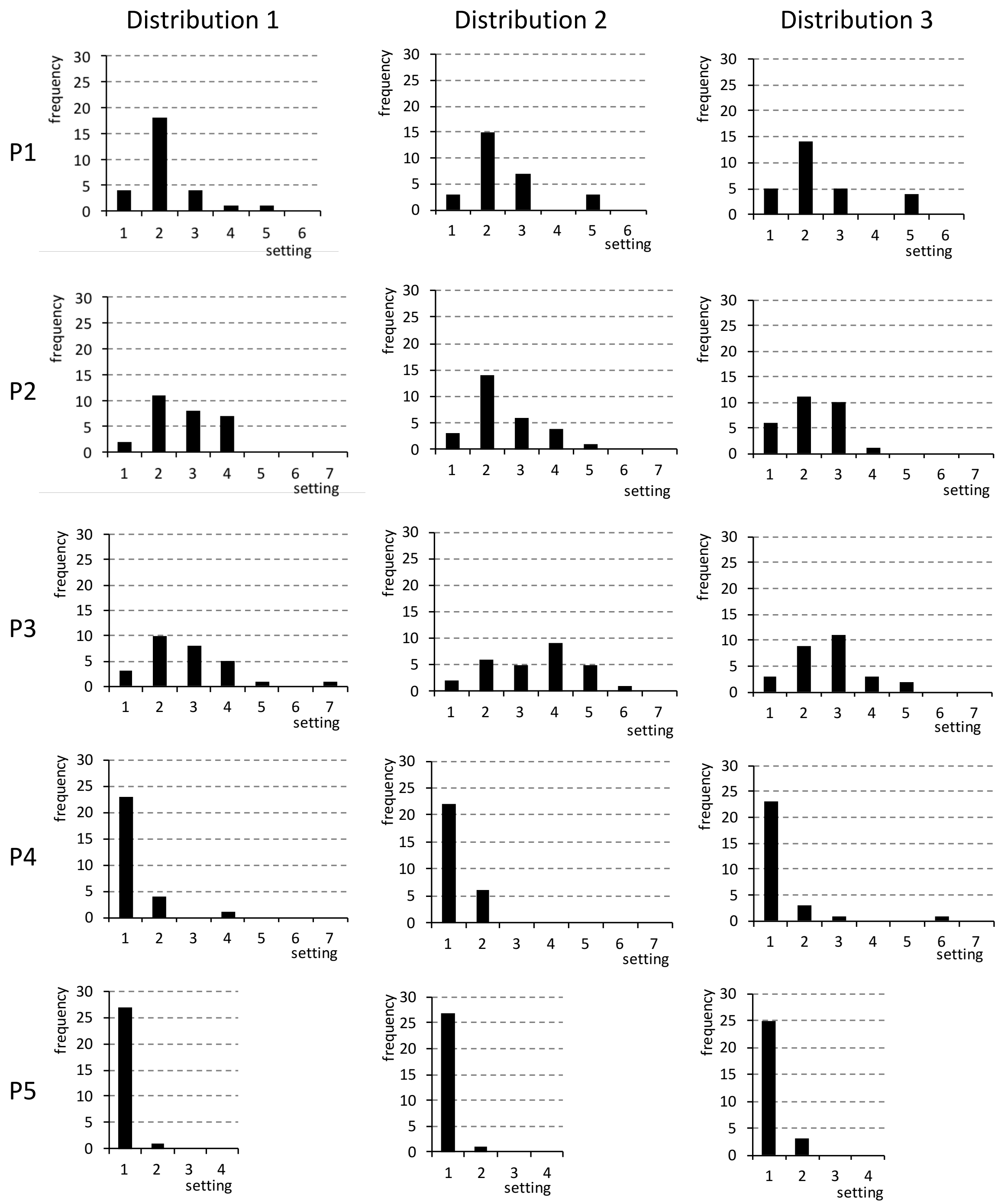

Figure 6.4 Distributions of recommended parameter settings for Madison, WI

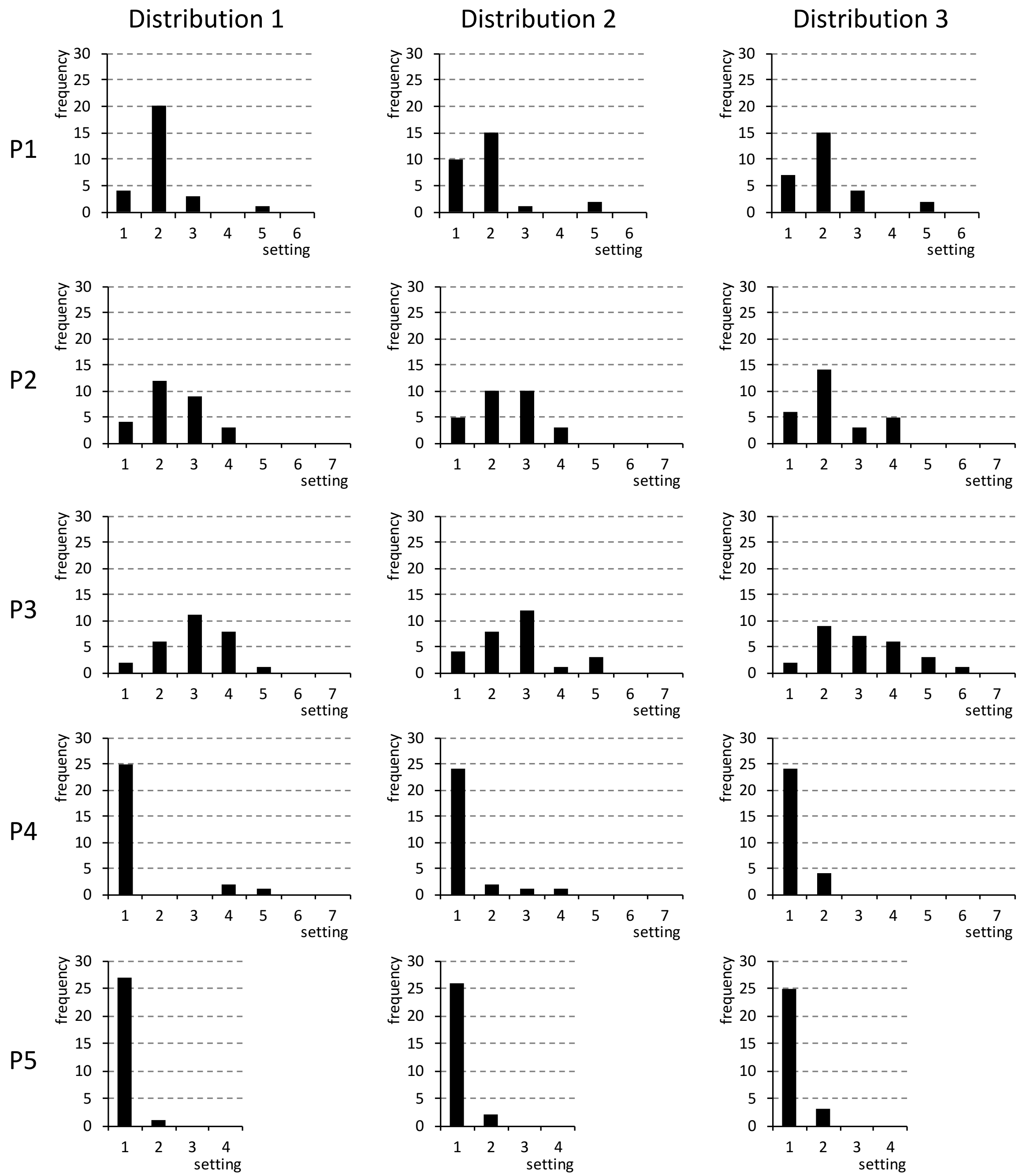

Figure 6.5 Distributions of recommended parameter settings for Washington, D.C.

6.2.1 Parameter 1 (glazing type)

For parameter 1 (glazing type), setting no. 2 with a U-value of 1.57 W/m^{2}K, a SHGC value of 0.31, and a light transmittance value of 0.62 is recommended most frequently for all three locations. The second most recommended parameter setting is no. 1 (U-value of 2.20 W/m^2K, SHGC of 0.20, light transmittance of 0.25, and \$365/m^2 of investment cost) for Chicago, IL and Washington, D.C. For Madison, WI, setting no. 3 (U-value of 1.20 W/m^2K, SHGC of 0.31, light transmittance of 0.62, and \$436/m^2) is either recommended second most frequently or ties with setting no. 1. This seems to result from the colder climate of Madison compared with the two other locations; that is to say, the better thermal performance of setting no. 3 offsets the increased investment cost in Madison's cold climate considering the 30-year LCC analysis. Setting no. 5 is recommended in a small number of optimization runs, and settings no. 4 and no. 6 are almost never recommended for all three locations. Overall, a clear tendency is found towards setting no. 2.

This results implies a possibility that a false conclusion, such as setting no. 5 is recommended, could have been generated if a single optimization run is conducted without the integration of the LHS method. As shown in Figures 6.3 through 6.5, this study generates output distributions instead of a single optimization result by integrating the LHS method, and therefore, a selected parameter setting can be said to be a robust result if there exists a clear tendency towards the particular setting. If the recommendations are relatively evenly distributed among parameter settings, it is more difficult to choose one particular setting, and the selection of a robust optimization result can be said to be riskier.

6.2.2 Parameter 2 (wall insulation)

For the second parameter, wall insulation, setting no. 2 (U-value of 0.46 W/m^2K) is the most often recommended parameter setting in all distributions for all three locations. The second most frequent recommendation is setting no. 3 (U-value of 0.37 W/m^2K) in most distributions. This seems to be because of the higher investment cost of setting no. 3 (\$14.8/m^2) than that of setting no. 2 (\$11.5/m^2), though setting no. 3 has a higher insulation level. Settings no. 6 and no. 7 have never been recommended from any optimization run. The recommendations in general are concentrated on the range of settings no. 1 through no. 4.

In Distributions 2 and 3 for Chicago, in Distribution 2 for Madison, and in Distribution 3 for Washington, D.C., there is a relatively clear tendency towards setting no. 2; in other words, the difference in the number of recommendations between setting no. 2 and the other settings is relatively large. However, in the rest of the distributions, the differences are not as big, and thus it is more difficult to find the optimal result based on the frequency of recommendations. Overall, a less clear tendency towards a particular parameter setting appears for Parameter 2 in comparison to Parameter 1.

6.2.3 Parameter 3 (roof insulation)

Parameter 3 shows the least clear tendency towards one parameter setting among all five parameters used in this study. The recommendations for Parameter 3 are most dispersed. Every parameter setting receives at least one recommendation, while the majority of recommendations are concentrated within the range of settings no. 1 to no. 5. For example, in distribution 3 for Washington, D.C. (Figure 6.5), six parameter settings out of seven have been recommended at least once, and no parameter setting has a highly larger number of given recommendations than the rest of the settings.

Among the total of nine distributions for the three cities, setting no. 3 (U-value of 0.37 W/m^{2}K and \$14.8/m^2 of investment cost) is the most often recommended setting in five distributions, but setting no. 2 (U-value of 0.46 W/m^{2}K and \$11.5/m^2 of investment cost) is more frequently recommended than no. 3 in three other distributions. There also is not a big difference in the frequency of recommendations between setting no. 3 and no. 2. The relatively evenly distributed recommendations throughout the settings indicate that selecting the most recommended setting from the distribution may involve a higher risk of not making a robust decision. This also implies that the varying input variables, in which the uncertainty in user behaviors is included, have a greater impact on Parameter 3 compared to other parameters.

6.2.4 Parameter 4 (floor insulation)

The recommendations for Parameter 4, which is floor insulation, are primarily focused on parameter setting no. 1 (U-value of 0.7 W/m^{2}K and \$8.13/m^2 of investment cost) for Chicago, Madison, and Washington, D.C. The second most recommended setting is no. 2 (U-value of 0.46 W/m^{2}K and \$11.5/m^2 of investment cost), but there is a large difference in the number of recommendations between settings no. 1 and no. 2. Some other settings also receive a few recommendations, but the frequencies of recommendations for those settings are negligible compared with the very highly recommended setting no. 1. Unlike Parameter 3, this result for Parameter 4 indicates that it is robust to choose setting no. 1 for the floor insulation, and the uncertainty included in the varying input variables has a marginal influence on this parameter.

6.2.5 Parameter 5 (air tightness)

Parameter 5 (air tightness) has the least dispersed recommendations among all five optimization parameters. Similar to Parameter 4, setting no. 1 is clearly most recommended in all distributions for all three locations. Setting no. 2 is recommended just a few times, and settings no. 3 and no. 4 have never been recommended from any optimization runs. The difference between the most recommended setting and the second most recommended setting is hence the biggest among all five parameters. As a result, the risk in choosing setting no. 1 (0.25 of ACH) is very low. Just like Parameter 4, the optimization result indicates that the recommendation is very robust. Considering varying input variables, this implies that setting no. 1 is the optimal parameter setting for air tightness of the building regardless of user behaviors. This might be derived from the comparatively low investment cost of setting no. 1 ($4.5/m^2$) despite the setting's relatively high air change rate compared to other settings.

6.3 Biased Optimization Results

Supplementary optimization runs to see the effect of user behaviors of very high energy demand and very low energy demand are performed by using biased input variables. The biased optimization is conducted for one location, Chicago, IL. The samples of input variables are arbitrarily biased to reflect high internal heat gain values or low internal heat gain values. The results of two sampling runs are combined to develop one distribution of the biased optimizations. Therefore, each distribution has results from 28 optimization runs.

In general, the mean value of the LCC from the biased runs with input variables of high energy demand is significantly higher than the mean value of the LCC of the LHS runs without biased variables. This can be easily predicted that a household of high energy demand uses a lot of energy and thus ends up with a high LCC. On the other hand, the mean value of the LCC from the biased runs with input variables of low energy demand is smaller than the mean value of the LCC of the LHS runs without biased variables. The tendency towards the lower LCC for a household of low energy demand can be explained by the fact that the thermostat settings for heating and cooling might have been shifted to a larger accepted comfort range.

The results for the recommended parameter settings, however, are less obvious than expectation in terms of the difference between the biased optimization and the LHS runs. Figure 6.6 shows the frequency of recommendation for the parameter settings from the biased optimizations for Chicago.

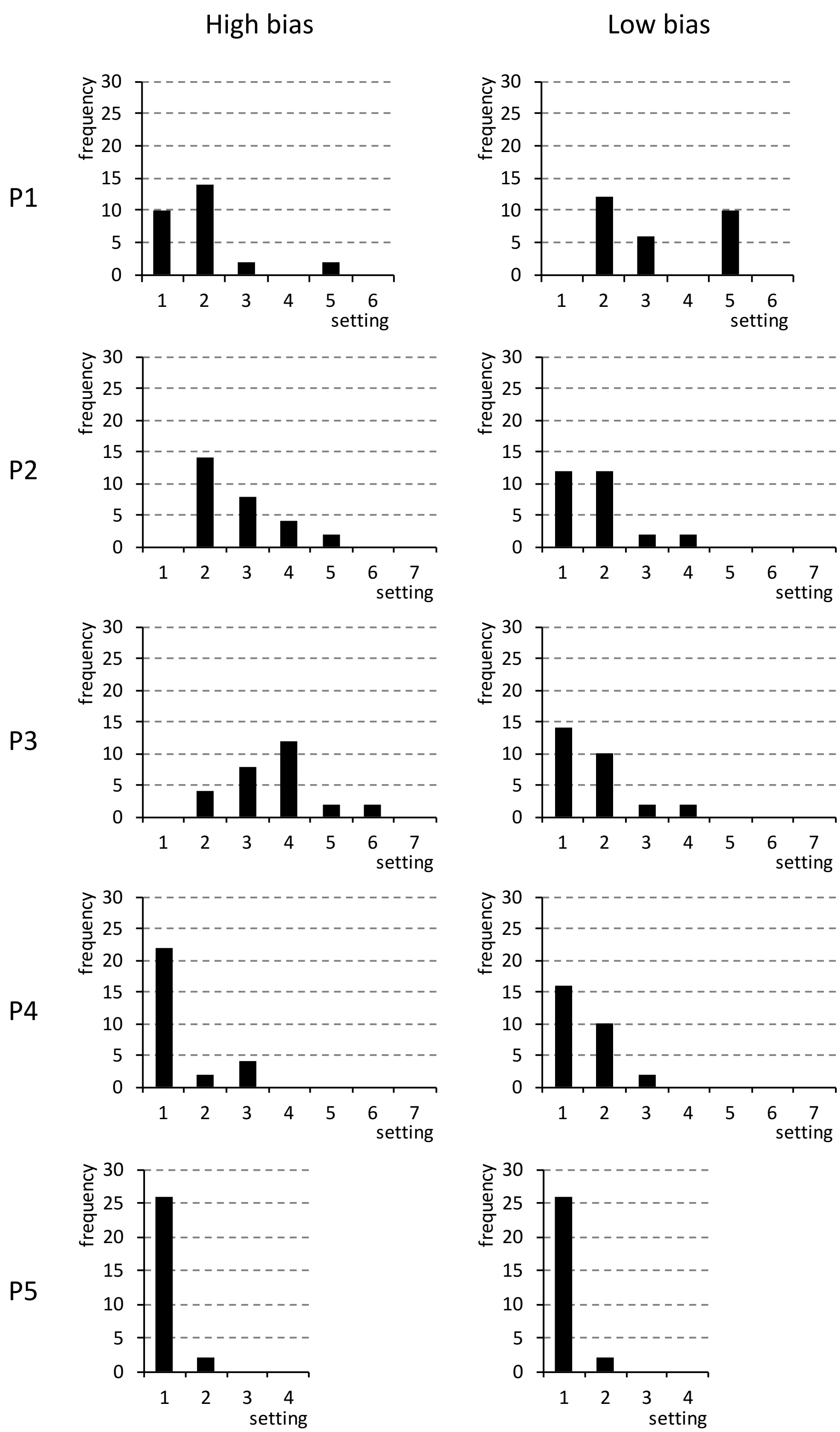

Figure 6.6 Distributions of recommended parameter settings from biased optimization runs for Chicago, IL

For Parameter 1 (glazing type), the biased optimization runs recommend the same parameter setting as the LHS runs. Parameter setting no. 2 receives the highest frequency of recommendations for both high and low bias optimization runs. Especially, the high bias case shows the exactly same pattern as the results from the LHS runs; setting no. 2 is most recommended, setting no. 1 is second most recommended, setting no. 3 and no. 5 are recommended just a few times, and settings no. 4 and no. 6 are never recommended. Setting no. 2 is most recommended for the low bias optimizations as well, but it is notable that setting no. 5 is also recommended a lot, and setting no. 1 is never recommended in this case. Setting no. 3 is also recommended more often than other two cases. Once again, this seems to be derived from occupants' low energy demand. The combined effect of higher thermal performance of glazing and occupants' energy-efficient behaviors, such as lowering the thermostat setpoint temperature for heating and raising the setpoint temperature for cooling, may offset the increased investment cost for the high performance glazing types. Overall, the tendency towards parameter setting no. 2 is less evident from biased optimization runs than the LHS runs.

For Parameter 2 (wall insulation), setting no. 2 is most recommended for biased optimization runs just like the LHS runs. However, setting no. 1 is just as frequently recommended as no. 2 for the low bias optimization whereas never recommended for the high bias optimization. The recommendations for Parameter 3 (roof insulation) are most dispersed among its parameter settings for the LHS runs, and also for the biased optimization runs. The frequency of recommendation for Parameter 4 (floor insulation) and 5 (air tightness) are very similar to those results in the LHS runs. Parameter setting no. 1 is most often recommended in all sampling runs. However, for the low bias optimization runs, the difference in the number of recommendations between setting no. 1 and the second most recommended setting is relatively smaller than that of other optimization runs.

To sum up, the mean value of the absolute energy demand and LCC of the two types of sampling runs (the biased optimization and the LHS runs) are significantly different. However, the tendencies towards particular parameter settings for each parameter in the distributions of the optimization results are similar, especially for the high bias optimization. For the low bias optimization, still somewhat similar tendencies are shown, but there are also some notable differences from the high bias optimization and the LHS runs.

6.4 Robust Selection of Optimization Results

Various sources of uncertainty and the influence of varying user behavior-related input variables on the simulation-based optimization results using the LHS method are investigated in the precious sections. This is only part of this research. A decision-making framework is needed for decision makers to utilize this useful additional information [87]. The recommendations for parameter settings as optimization results need to be compared on the basis of a scientific and valid decision-making framework to support robust decision-making.

6.4.1 Based on the frequency and the test of proportion

This study generates output distributions and uses them for the result analysis instead of a single optimization result. This is done by using varying input distributions and integrating the LHS method. A particular parameter setting that is recommended by the optimization process can be said to be robust when a clear tendency towards the setting is found. This means that the recommendation for a parameter setting is regarded as robust when the difference of the frequency between the most frequently recommended setting and the other settings is relatively large. The recommendation can be described as riskier when this difference is relatively small. Thus, a reasonable evaluation standard is necessary to decide whether the difference is large or small.

In this study, the test of proportion is used as the standard to examine if the difference can be regarded large enough to tell that choosing the most often recommended parameter setting is a robust decision. If the difference is evaluated to have a statistical significance, the most frequently recommended parameter setting is selected as an optimal solution for the parameter. The concept, calculation, and flow of the test of proportion are explained in '5.4.2 Test of proportion.' The test is conducted by using an online statistical software tool [159]. If, p-value is equal to or smaller than a, the difference can be described to be statistically significant, and thus the most often recommended parameter setting is selected. If p-value is larger than a, no statistically significant difference exists between the two settings. Then, the settings need to be evaluated by using the next step, the Hurwicz criterion. The value of a is defined as .05.

Figure 6.7 shows the recommendations for parameter settings of each parameter for Chicago, Madison, and Washington, D.C. The recommendations of the three distributions shown in Figures 6.3 through 6.5 are combined, so each graph in Figure 6.7 has 84 recommendations as the optimization results. The test of proportion is performed for each recommendation, and the recommendations that do not have a statistically significant difference between them are marked with an arrow above them in the graphs.

For Parameters 1, 4, and 5, there exists an obvious tendency toward the most often recommended parameter setting: setting no. 2 for Parameter 1, setting no. 1 for Parameters 4 and 5. In other words, a statistically significant difference is found between the most recommended setting and the rest of the settings as a result of the test of proportion. In these cases, the most frequently recommended parameter setting of each parameter can be selected as a robust optimal result. As discussed in '6.2 Optimization Results for Parameters,' Parameter 2 and 3 have the least clear tendency towards a particular parameter setting, and the recommendations are the most dispersed among the five optimization parameters. For Parameter 2, two parameter settings (setting no. 2 and no. 3) are identified not to have a statistically significant difference between them for Madison, WI and Washington, D.C. For Parameter 3, no statistical significance is found between two parameter settings (setting no. 2 and no. 3) for Chicago, IL and Washington, D.C. and between three parameter settings (setting no. 2, no. 3, and no. 4) for Madison, WI. Therefore, these parameter settings cannot be chosen as an optimal result based on the frequency of recommendations and need further examination using a decision theory.

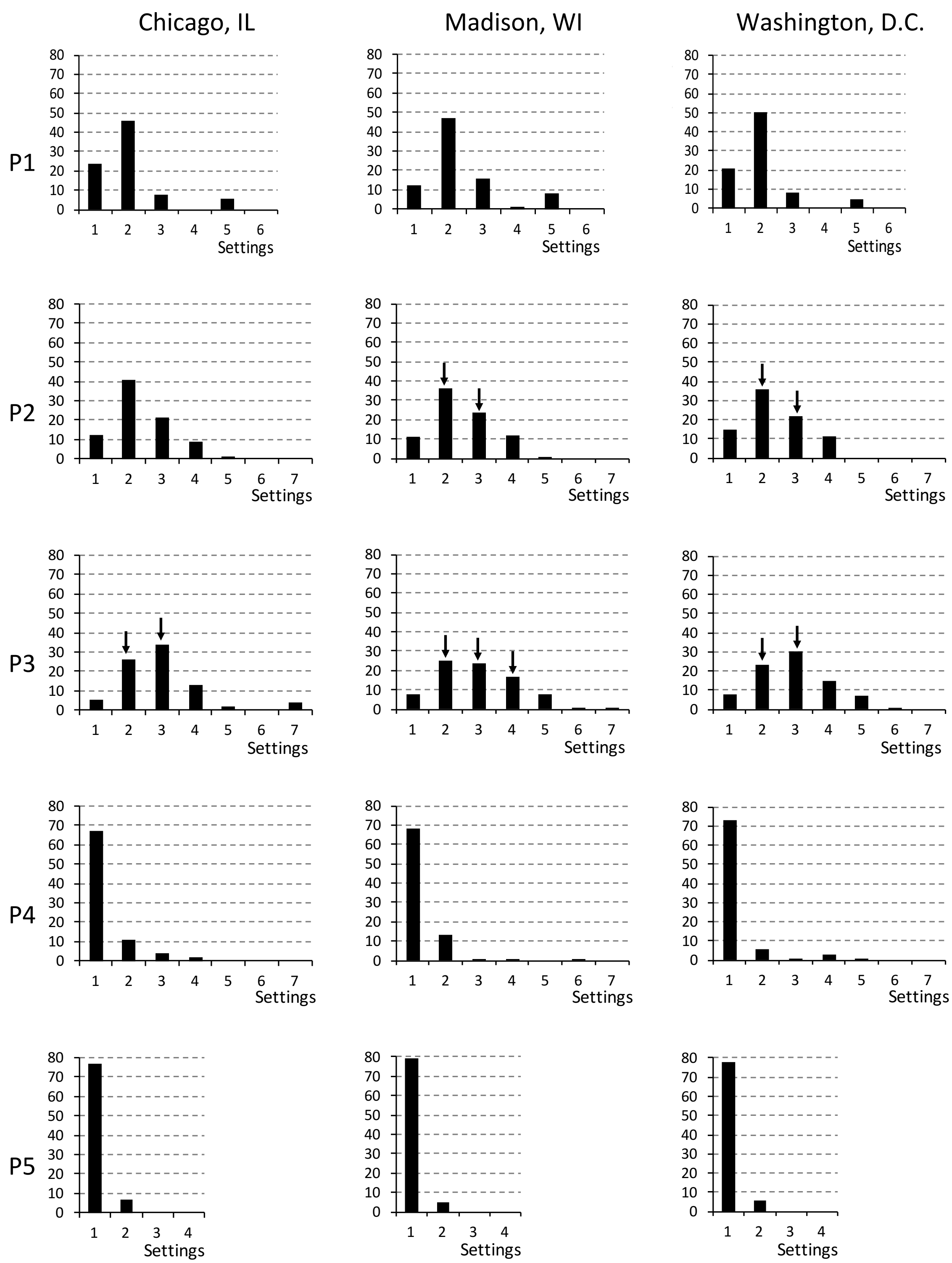

Figure 6.7 Results of the test of proportion showing the statistical significance between parameter settings

6.4.2 Application of the Hurwicz criterion

Probabilistic decision theories, including utility theory and regret theory, cannot be used in this study because the result of this study does not have all the necessary components of probabilistic decision theories. In fact, it is one of the major disadvantages that a lot of information is required to utilize a probabilistic decision theory. Instead, a non-probabilistic decision criterion is applied to the result of this study. Among various non-probabilistic decision rules (decision-making under uncertainty) introduced in Chapter 3, the Hurwicz criterion is used to choose one optimal parameter setting between two or three settings of Parameters 2 and 3 that need to be compared. The major advantage of the Hurwicz criterion is that it allows a decision maker to have his or her own personal point of view towards an optimistic or pessimistic condition. In this study, for the value of the coefficient of optimism, H=0.3 is used for a pessimistic decision maker, and H=0.7 is used for an optimistic decision maker. Finally, H=0.5 is used for a risk-neutral decision maker.

For Chicago, IL, only one parameter (Parameter 3) needs an application of the Hurwicz decision rule to compare parameter settings no. 2 and no. 3. Figure 6.8 shows the distributions of the LCC when settings no. 2 and no. 3 are recommended for Parameter 3. The LCC values are considered as the payoffs for each alternative (settings no. 2 and no. 3). The maximum and minimum payoffs for setting no. 2 are \$119.20/m^2 and \$209.90/m^2, respectively. Note that the maximum payoff has the smaller value (optimistic) and the minimum payoff has the larger value (pessimistic) since these values are about the cost. For setting no. 3, the maximum and minimum payoffs are $130.89/m^2$ and $195.38/m^2$, respectively. For an optimistic decision maker, the expected values for parameter settings no. 2 and no. 3 are calculated as:

$$\text{Setting no. 2: } (0.3\times\$209.90/\text{m}^2) + (0.7\times\$119.20/\text{m}^2) = \$146.41/\text{m}^2$$

$$\text{Setting no. 3: } (0.3\times\$195.38/\text{m}^2) + (0.7\times\$130.89/\text{m}^2) = \$150.24/\text{m}^2$$

Therefore, an optimistic decision maker will choose setting no. 2, which generates a smaller expected LCC based on the Hurwicz criterion, for Parameter 3 for Chicago, IL.

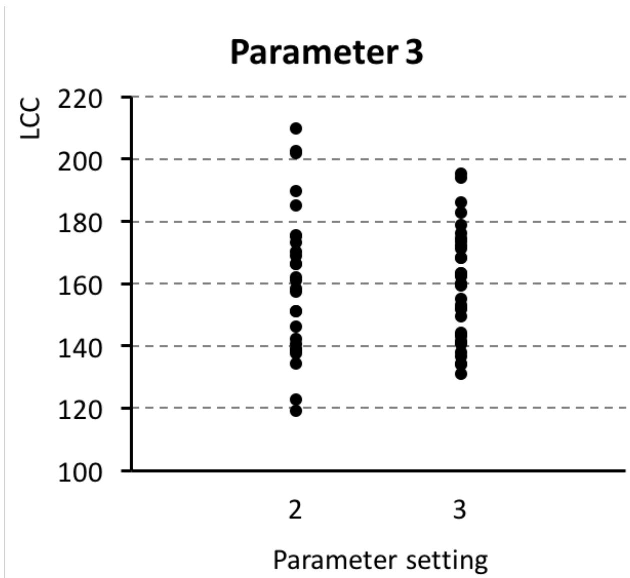

Figure 6.8 LCC distributions for setting no. 2 and no. 3 of Parameter 3 for Chicago, IL

On the other hand, a pessimistic decision maker calculates the expected values as:

$$\text{Setting no. 2: } (0.7\times\$209.90/\text{m}^2) + (0.3\times\$119.20/\text{m}^2) = \$182.69/\text{m}^2$$

$$\text{Setting no. 3: } (0.7\times\$195.38/\text{m}^2) + (0.3\times\$130.89/\text{m}^2) = \$176.03/\text{m}^2$$

Hence, setting no. 3 is a more optimal option for the pessimistic decision maker.

Lastly, in the case of a risk-neutral decision maker, the expected values are calculated as:

$$\text{Setting no. 2: } (0.5\times\$209.90/\text{m}^2) + (0.5\times\$119.20/\text{m}^2) = \$164.55/\text{m}^2$$

$$\text{Setting no. 3: } (0.5\times\$195.38/\text{m}^2) + (0.5\times\$130.89/\text{m}^2) = \$163.14/\text{m}^2$$

For the risk-neutral case, setting no. 3 has a smaller expected LCC value, but the difference of the expected LCC values between settings no. 2 and no. 3 is relatively small compared to two other cases. This is because H=0.5 is used for the risk-neutral case, which eventually produces the mean of the maximum and minimum LCC values.

Likewise, the Hurwicz criterion is applied to two parameters (Parameters 2 and 3) for Madison, WI. Two parameter settings (no. 2 and no. 3) are compared for Parameter 2, and three settings (no. 2, no. 3, and no. 4) are evaluated for Parameter 3. Tables 6.2 and 6.3 summarize the calculation results of the expected values for optimistic (H=0.7), pessimistic (H=0.3), and risk-neutral (H=0.5) decision makers, respectively. Regardless of the H value, which stands for a decision maker's personal view, setting no. 2 always has a better expected value. Thus, setting no. 2, which has the highest recommendations, is identified to be selected as an optimal parameter setting for Parameter 2. Similarly, for Parameter 3, setting no. 2 always has the smallest expected LCC value among the three parameter settings, and therefore, it is appropriate to select parameter setting no. 2 as an optimal result.

Table 6.2 Results of expected LCC for Parameter 2 for Madison, WI

Unit: $\$/m^2$

		Payoffs	
		Setting no. 2	Setting no. 3
Maximum		117.17	128.11
Minimum		198.51	249.84
		Expected values	
Hurwicz index, H	0.7	141.57	164.63
	0.3	174.11	213.32
	0.5	157.84	188.98

Table 6.3 Results of expected LCC for Parameter 3 for Madison, WI

Unit: $\$/m^2$

		Payoffs		
		Setting no. 2	Setting no. 3	Setting no. 4
Maximum		117.17	129.09	134.39
Minimum		194.38	209.40	249.84
		Expected values		
Hurwicz index, H	0.7	140.33	153.18	169.02
	0.3	171.21	185.31	215.21
	0.5	155.77	169.25	192.12

For Washington, D.C., settings no. 2 and no. 3 are examined for Parameters 2 and 3. Tables 6.4 and 6.5 summarize the calculation results of the expected values for each decision maker. For Parameter 2, setting no. 3 would be selected as an optimal parameter setting by all decision makers of three different risk-taking attitudes. For Parameter 3, setting no. 2 has a better LCC value for a pessimistic decision maker, while setting no. 3 is a more optimal option for an optimistic decision maker and a risk-neutral decision maker. However, the differences of the expected values between the two settings are very marginal for Parameter 3 for Washington, D.C.

Table 6.4 Results of expected LCC for Parameter 2 for Washington, D.C.

Unit: \$/m^2

		Payoffs	
		Setting no. 2	Setting no. 3
Maximum		118.88	121.98
Minimum		217.87	204.30
		Expected values	
Hurwicz index, H	0.7	148.57	146.68
	0.3	188.17	179.61
	0.5	168.37	163.14

Table 6.5 Results of expected LCC for Parameter 3 for Washington, D.C.

Unit: \$/m^2

		Payoffs	
		Setting no. 2	Setting no. 3
Maximum		121.98	118.88
Minimum		207.50	209.21
		Expected values	
Hurwicz index, H	0.7	147.64	145.98
	0.3	181.85	182.11
	0.5	164.74	164.04

CHAPTER 7

CONCLUSIONS

This study investigates the effect of uncertainty in user behaviors on the simulation-based optimization process using a genetic algorithm (GA) and the Latin hypercube sampling (LHS) method. A decision-making framework to support robust decision-making from the output distributions of optimization results is also introduced. The major findings are based on the optimization results and the application of the decision-making framework.

7.1 Findings

This study identifies the influence of the user behavior-related input variables on the robustness of the optimization process. The results show that the robustness of the recommendations generated by the building optimization algorithm is relatively high when the optimization algorithm is run repeatedly with a range of possible input variables. The proposed decision-making framework using the frequency of recommendation, the test of proportion, and the Hurwicz decision criterion is applicable to the generated optimization results.

Three locations

The optimization and sampling runs for Madison, WI and Washington, D.C. are mainly carried out in order to verify the conclusions for Chicago, IL. A comparison of the frequency and dispersion of recommendation for the five parameters between the three locations that is discussed in 'Chapter 6 Results and Analysis' shows that the conclusions drawn for Chicago, IL are also valid for the other two cities. In most cases, the recommendations produced by the combined optimization algorithm for three locations show similar results except for a few minor cases. This points out that the research method proposed in this study, that is the combined optimization algorithm and the LHS method, is rational to be used for building optimization while implementing the stochastic approach by integrating the uncertainty in user behavior-related input variables.

Parameters and parameter settings

Overall, optimization results demonstrate a clear tendency towards an optimal parameter setting or a range of settings in spite of varying input variables. The most obvious tendency towards a particular parameter setting (setting no. 1) is found for Parameters 4 (floor insulation) and 5 (air tightness) for all three locations. A relatively clear tendency towards setting no. 2 is observed for Parameter 1 (glazing type). The tendency is less clear for Parameter 2 (wall insulation), and most of the recommendations are concentrated into parameter settings no. 2 and no. 3. Parameter 3 (roof insulation) has the most dispersed recommendations throughout the seven parameter settings, but there is still a tendency toward a range of parameter settings (no. 2, no. 3, and no. 4).

A clear tendency towards a particular parameter setting implies that the influence of varying user behavior-related input variables on the parameter is small. On the other hand, the more the recommendations are dispersed, the greater impact of varying input variables on that parameter is implied.

Biased optimizations

Biased optimizations are run to see the influence of biased input variables, that reflect occupant behaviors of an exceptionally high or significantly low energy demand. In general, low bias optimization runs demonstrate less obvious tendency towards the most recommended parameter setting. This implies that energy-efficient user behaviors have a greater impact on the recommendations of building materials to achieve optimal results. It seems that occupant behaviors of a higher energy demand have less impact on selection of optimal parameter settings and contribute more to the increased energy consumption and LCC.

The comparison of the results from the optimization runs using biased input variables and from the optimization runs using input variables generated by the LHS method demonstrates that the proposed optimization process (genetic algorithm combined with LHS) can provide reliable results.

Decision-Making Framework

The frequency of recommendation is a good indicator for its robustness to be selected as the final optimal choice when a large difference exists between the most frequently recommended parameter setting and other settings. The test of proportion is appropriately utilized as a tool to identify whether the difference is statistically significant.

The Hurwicz criterion provides an objective basis to evaluate the robustness of selecting an optimal solution when the frequency of recommendation cannot be used because of lack of the statistical significance. A decision maker's risk-taking attitude can be reflected in the evaluation by adjusting the value of the coefficient of optimism.

7.2 Contributions

This dissertation contributes to the field of building optimization as it proposes a method to integrate uncertainty in input variables and shows the method generates reliable results. A new technique to integrate uncertainty in input variables into simulation-based optimization is introduced. Probability distributions are used instead of a single deterministic value as inputs, and LHS is performed to define varying sample sets of input variables. A genetic algorithm with input variables reflecting varying occupant behaviors is repeatedly run. The proposed approach is applied to a typical U.S. single-family house for three locations (Chicago, IL; Madison, WI; and Washington, D.C.) in the United States. The reliability of the optimization results is found by comparing the results from three different locations as well as comparing the results from LHS runs and biased optimization runs.

A decision-making framework that is applicable to the results of the presented method, which generates output distributions instead of a single optimal result, is also proposed and proves its applicability. The proposed decision-making framework provides a decision maker with a scientific and valid foundation for robust decision-making as it helps in selecting an optimal solution. It verifies the robustness of produced recommendations. The framework is expected to support building design and renovation projects that use an optimization process for making decisions. As a result, more reliable and practical use of optimization processes in the building industry would be promoted.

Computation time has been considerably reduced by using the LHS method to less than it would be needed if a random sampling Monte Carlo method is used. The high computational cost has been one of the major disadvantages of building optimization. This research contributes to reducing computation time using the LHS method while improving sampling efficiency and convergence.

While this study does not include all potential input variables with uncertainty in a building optimization process, it provides significant insight into the role of input variables with uncertainty in the building optimization process.

7.3 Directions for Future Research

This research deals with the uncertainty in user behavior-related input variables. There are various sources of uncertainty in the simulation-based building optimization process, and future research may expand its scope to include a wider variety of uncertainty sources. However, because having more number of input variables makes an optimization problem more complex and brings about increased computation time, it is important to limit the scope to a proper range that a study can handle.

For statistical analyses, a higher accuracy is generally achieved with a larger number of samples. The relation between the sample size and optimization results can be investigated. It would be intriguing to see how the results would change if more simulation runs are conducted.

According to the results of this study, Parameters 2 (wall insulation) and 3 (roof insulation) turn out to be most vulnerable to the uncertainty in input variables. While Parameters 1 (glazing type), 4 (floor insulation), and 5 (air tightness) are not considerably influenced by varying user behaviors and have a clear tendency towards an optimal parameter setting, the recommendations for Parameters 2 and 3 are dispersed throughout available parameter settings being affected by varying input variables. Future research may investigate the reason why these parameters are more influenced by user behaviors than others.

Finally, an investigation into the effect of energy efficient occupant behaviors on building optimization results can be another research topic. The results of the biased optimization runs with biased input variable of a low energy demand show that energy efficient user behaviors have a greater impact on the optimization results than user behaviors of a high energy demand. The current trend of building codes is in the direction towards more energy efficient and sustainable architecture. Considering that newly constructed or renovated buildings will be built with materials of higher thermal performance, it is worth investigating how occupants' energy efficient behaviors influence the optimal building material selection.

APPENDICES

APPENDIX A. Average schedules for internal loads

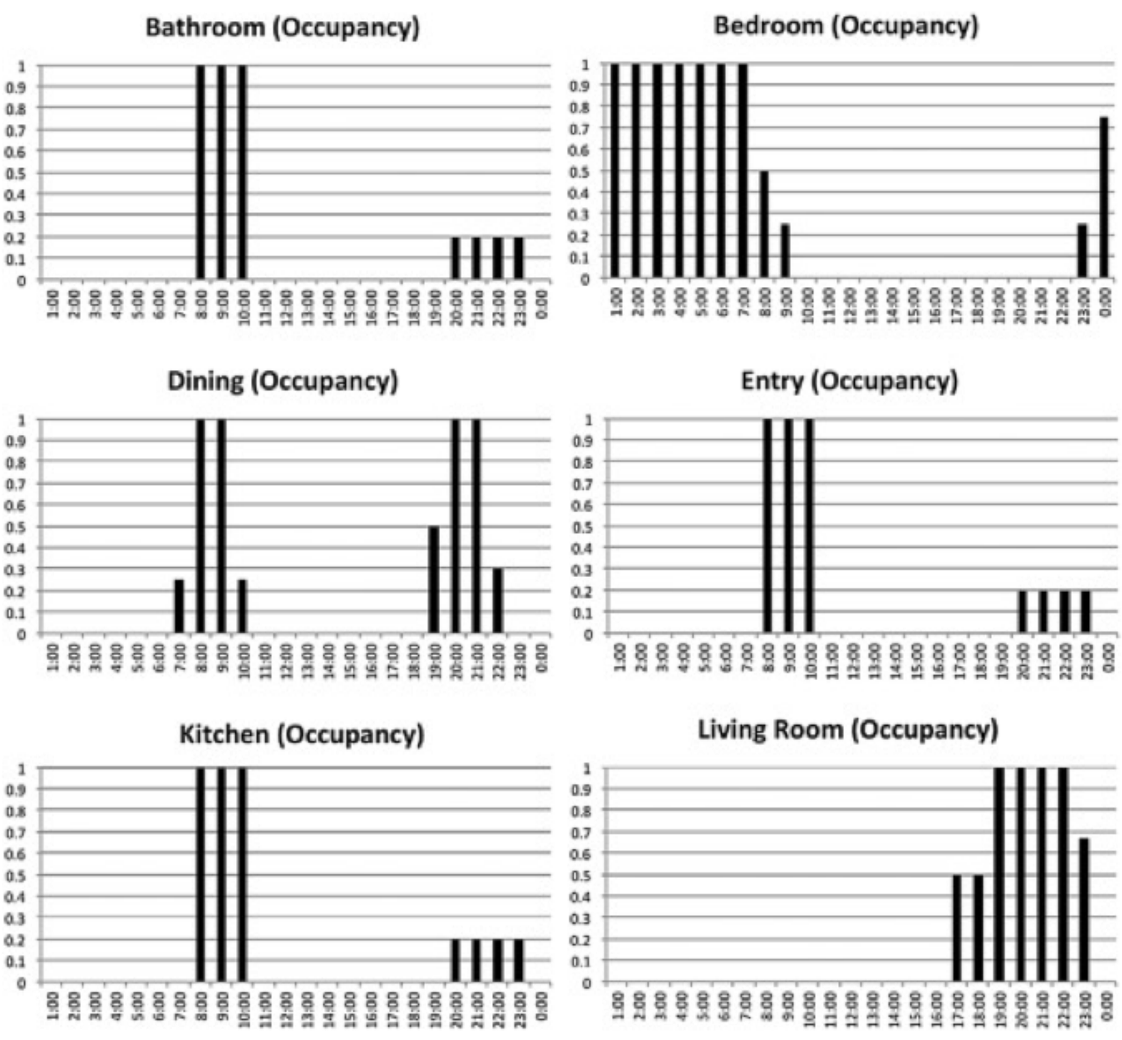

Figure A.1: Average schedules for occupancy

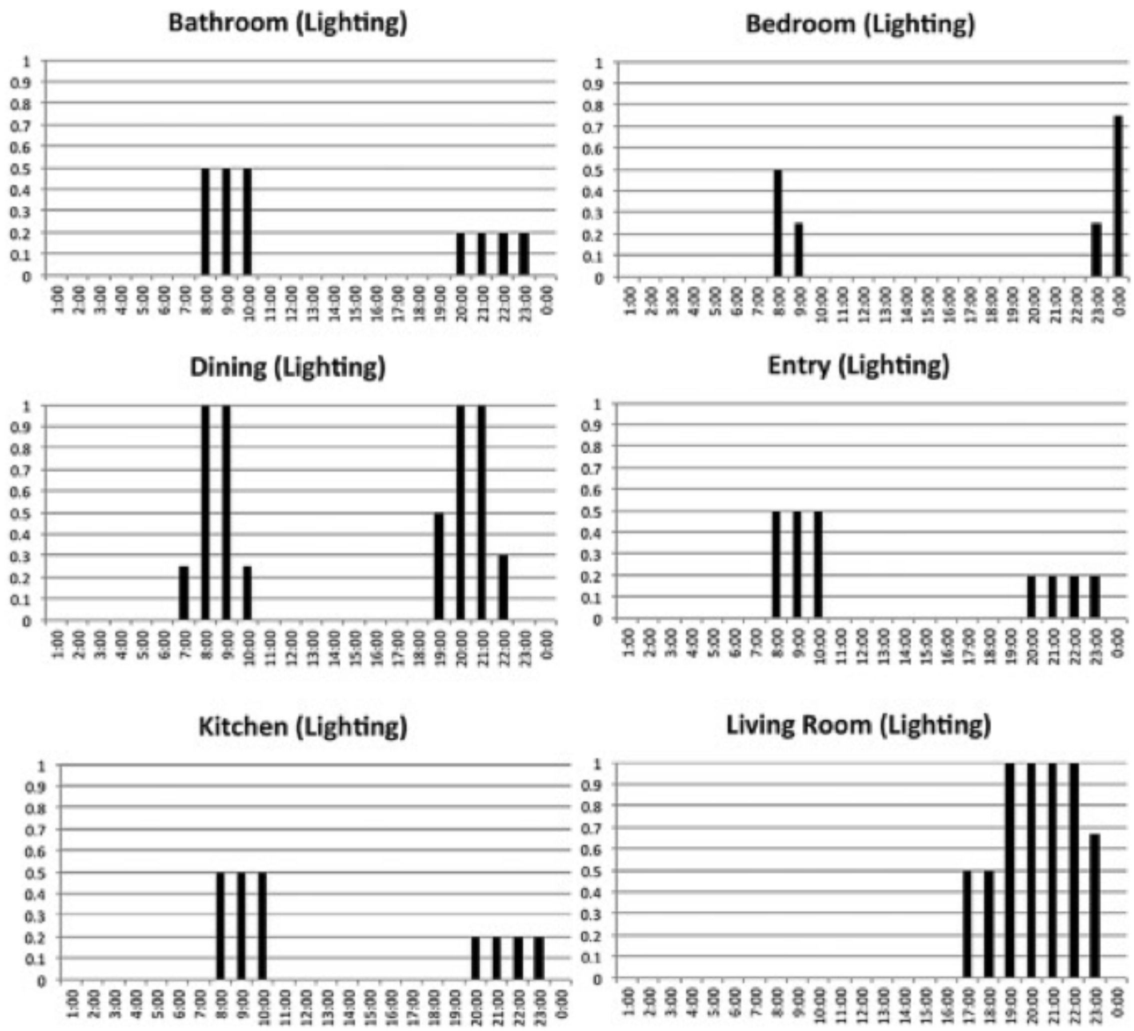

Figure A.2: Average schedules for artificial lighting

APPENDIX B. Hourly internal load schedules

Table B.1 Occupancy schedule in living room (%)

Time	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0.1	0.1	0.4
17	0	0	0	0	0.1	0.3	0.5	0.5	0.5	0.5	0.5	0.6	0.7	0.7
18	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.7	0.8	0.9	1	1
19	1	1	1	1	1	1	1	1	1	1	1	1	1	1
20	1	1	1	1	1	1	1	1	1	1	1	1	1	1
21	1	1	1	1	1	1	1	1	1	1	1	1	1	1
22	1	1	1	1	1	1	1	1	1	1	1	1	1	1
23	0	0.2	0.4	0.6	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table B.2 Occupancy schedule in kitchen (%)

Time	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
8	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.6	0.7	0.8
9	0	0	0.2	0.3	0.3	0.4	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.3	0.4	0.5	0.6	0.7	0.8
21	1	1	1	1	1	1	1	1	1	1	1	1	1	1
22	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
23	0	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table B.3 Occupancy schedule in dining room (%)

Time	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
8	1	1	1	1	1	1	1	1	1	1	1	1	1	1
9	0.5	0.7	1	1	1	1	1	1	1	1	1	1	1	1
10	0	0	0	0	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.4	0.6
11	0	0	0	0	0	0	0	0	0	0	0	0	0.2	0.2
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0.2	0.3	0.3	0.5
19	0	0	0	0.1	0.3	0.4	0.5	0.5	0.7	0.9	0.9	1	1	1
20	0.7	0.9	0.9	1	1	1	1	1	1	1	1	1	1	1
21	1	1	1	1	1	1	1	1	1	1	1	1	1	1
22	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table B.4 Occupancy schedule in circulation area (%)

Time	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0.1	0.1	0.2	0.2	0.3	0.3	0.4	0.4	0.5	0.5	0.6	0.6	0.7	0.7
9	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
22	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
23	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table B.5 Occupancy schedule in bedroom 1 (%)

Time	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1	1	1	1	1	1
3	1	1	1	1	1	1	1	1	1	1	1	1	1	1
4	1	1	1	1	1	1	1	1	1	1	1	1	1	1
5	0.5	0.7	1	1	1	1	1	1	1	1	1	1	1	1
6	0.5	0.5	0.7	0.7	0.7	1	1	1	1	1	1	1	1	1
7	0.2	0.2	0.2	0.2	0.5	0.5	0.5	0.5	0.5	0.7	1	1	1	1
8	0	0	0	0	0.2	0.2	0.2	0.2	0.5	0.5	0.5	0.5	0.5	0.7
9	0	0	0	0	0	0	0	0	0	0	0.2	0.2	0.2	0.2
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0.2	0.2	0.2
23	0	0	0	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.7	1
24	0	0.3	0.3	0.5	0.5	0.5	0.8	0.8	0.8	0.8	0.8	0.8	1	1

Table B.6 Occupancy schedule in bedroom 2 (%)

Time	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1	1	1	1	1	1
3	1	1	1	1	1	1	1	1	1	1	1	1	1	1
4	1	1	1	1	1	1	1	1	1	1	1	1	1	1
5	0.5	0.7	1	1	1	1	1	1	1	1	1	1	1	1
6	0.5	0.5	0.7	0.7	0.7	1	1	1	1	1	1	1	1	1
7	0.2	0.2	0.2	0.2	0.5	0.5	0.5	0.5	0.5	0.7	1	1	1	1
8	0	0	0	0	0.2	0.2	0.2	0.2	0.5	0.5	0.5	0.5	0.5	0.7
9	0	0	0	0	0	0	0	0	0	0	0.2	0.2	0.2	0.2
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0.2	0.2	0.2
23	0	0	0	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.7	1
24	0	0.3	0.3	0.5	0.5	0.5	0.8	0.8	0.8	0.8	0.8	0.8	1	1

Table B.7 Occupancy schedule in bathroom (%)

Time	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
8	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
9	0	0.1	0.2	0.2	0.3	0.4	0.4	0.5	0.5	0.5	0.5	0.5	0.5	0.5
10	0	0	0	0	0	0	0	0.1	0.2	0.2	0.3	0.3	0.4	0.5
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0.1	0.1	0.2	0.2	0.2
19	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
20	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
21	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table B.8 Lighting schedule in living room (%)

Time	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0.1	0.1	0.4
17	0	0	0	0	0.1	0.3	0.5	0.5	0.5	0.5	0.5	0.6	0.7	0.7
18	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.7	0.8	0.9	1	1
19	1	1	1	1	1	1	1	1	1	1	1	1	1	1
20	1	1	1	1	1	1	1	1	1	1	1	1	1	1
21	1	1	1	1	1	1	1	1	1	1	1	1	1	1
22	1	1	1	1	1	1	1	1	1	1	1	1	1	1
23	0	0.2	0.4	0.6	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table B.9 Lighting schedule in kitchen (%)

Time	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
8	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.6	0.7	0.8
9	0	0	0.2	0.3	0.3	0.4	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.3	0.4	0.5	0.6	0.7	0.8
21	1	1	1	1	1	1	1	1	1	1	1	1	1	1
22	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
23	0	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table B.10 Lighting schedule in dining room (%)

Time	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
8	1	1	1	1	1	1	1	1	1	1	1	1	1	1
9	0.5	0.7	1	1	1	1	1	1	1	1	1	1	1	1
10	0	0	0	0	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.4	0.6
11	0	0	0	0	0	0	0	0	0	0	0	0	0.2	0.2
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0.2	0.3	0.3	0.5
19	0	0	0	0.1	0.3	0.4	0.5	0.5	0.7	0.9	0.9	1	1	1
20	0.7	0.9	0.9	1	1	1	1	1	1	1	1	1	1	1
21	1	1	1	1	1	1	1	1	1	1	1	1	1	1
22	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table B.11 Lighting schedule in circulation area (%)

Time	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0.1	0.1	0.2	0.2	0.3	0.3	0.4	0.4	0.5	0.5	0.6	0.6	0.7	0.7
9	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
22	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
23	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table B.12 Lighting schedule in bedroom 1 (%)

Time	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
9	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0.1	0.1
22	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.5	0.5
23	0.2	0.4	0.5	0.6	0.7	0.8	0.8	0.8	0.8	0.9	1	1	1	1
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table B.13 Lighting schedule in bedroom 2 (%)

Time	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
9	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0.1	0.1
22	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.5	0.5
23	0.2	0.4	0.5	0.6	0.7	0.8	0.8	0.8	0.8	0.9	1	1	1	1
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table B.14 Lighting schedule in bathroom (%)

Time	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
8	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
9	0	0.1	0.2	0.2	0.3	0.4	0.4	0.5	0.5	0.5	0.5	0.5	0.5	0.5
10	0	0	0	0	0	0	0	0.1	0.2	0.2	0.3	0.3	0.4	0.5
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0.1	0.1	0.2	0.2	0.2
19	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
20	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
21	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table B.15 Appliance power consumption schedule in living room (%)

Time	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0.1	0.1	0.4
17	0	0	0	0	0.1	0.3	0.5	0.5	0.5	0.5	0.5	0.6	0.7	0.7
18	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.7	0.8	0.9	1	1
19	1	1	1	1	1	1	1	1	1	1	1	1	1	1
20	1	1	1	1	1	1	1	1	1	1	1	1	1	1
21	1	1	1	1	1	1	1	1	1	1	1	1	1	1
22	1	1	1	1	1	1	1	1	1	1	1	1	1	1
23	0	0.2	0.4	0.6	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table B.16 Appliance power consumption schedule in kitchen (%)

Time	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
4	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
5	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
6	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
7	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
8	1	1	1	1	1	1	1	1	1	1	1	1	1	1
9	0.2	0.6	0.8	0.9	1	1	1	1	1	1	1	1	1	1
10	0.2	0.2	0.4	0.5	0.7	1	1	1	1	1	1	1	1	1
11	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3	0.4	0.6	0.8
12	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
13	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
14	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
15	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
16	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
17	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
18	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
19	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
20	0.2	0.2	0.2	0.2	0.4	0.4	0.4	0.4	0.4	0.7	0.7	0.8	0.8	1
21	0.4	0.6	0.8	0.9	1	1	1	1	1	1	1	1	1	1
22	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.5	0.5	0.5	0.5
23	0.3	0.3	0.3	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
24	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2

Table B.17 Appliance power consumption schedule in dining room (%)

Time	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
8	1	1	1	1	1	1	1	1	1	1	1	1	1	1
9	0.5	0.7	1	1	1	1	1	1	1	1	1	1	1	1
10	0	0	0	0	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.4	0.6
11	0	0	0	0	0	0	0	0	0	0	0	0	0.2	0.2
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0.2	0.3	0.3	0.5
19	0	0	0	0.1	0.3	0.4	0.5	0.5	0.7	0.9	0.9	1	1	1
20	0.7	0.9	0.9	1	1	1	1	1	1	1	1	1	1	1
21	1	1	1	1	1	1	1	1	1	1	1	1	1	1
22	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table B.18 Appliance power consumption schedule in circulation area (%)

Time	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0.1	0.1	0.2	0.2	0.3	0.3	0.4	0.4	0.5	0.5	0.6	0.6
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table B.19 Appliance power consumption schedule in bedroom 1 (%)

Time	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0.1	0.2	0.2
22	0	0	0	0.1	0.3	0.4	0.4	0.4	0.4	0.5	0.5	0.5	0.7	1
23	0	0.1	0.3	0.5	0.5	0.5	0.6	0.6	0.7	0.7	0.8	0.9	1	1
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table B.20 Appliance power consumption schedule in bedroom 2 (%)

Time	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0.1	0.2	0.2
22	0	0	0	0.1	0.3	0.4	0.4	0.4	0.4	0.5	0.5	0.5	0.7	1
23	0	0.1	0.3	0.5	0.5	0.5	0.6	0.6	0.7	0.7	0.8	0.9	1	1
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table B.21 Appliance power consumption schedule in bathroom (%)

Time	Samples													
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
8	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
9	0	0.1	0.2	0.2	0.3	0.4	0.4	0.5	0.5	0.5	0.5	0.5	0.5	0.5
10	0	0	0	0	0	0	0	0.1	0.2	0.2	0.3	0.3	0.4	0.5
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0.1	0.1	0.2	0.2	0.2
19	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
20	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
21	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0

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