

**FLEXIBILITY IN BUILDING DESIGN:
A REAL OPTIONS APPROACH AND VALUATION
METHODOLOGY TO ADDRESS RISK**

by

LARA V. GREDEN

B.E. Mechanical Engineering
University of Minnesota, 1999

M.S. Technology and Policy
M.S. Civil and Environmental Engineering
Massachusetts Institute of Technology, 2001

Submitted to the Department of Architecture
in Partial Fulfillment of the Requirements for the Degree of

DOCTOR OF PHILOSOPHY IN ARCHITECTURE: BUILDING TECHNOLOGY
at the
MASSACHUSETTS INSTITUTE OF TECHNOLOGY
June 2005

© Massachusetts Institute of Technology. All rights reserved.

Author: _____
Building Technology Program
April 29th, 2005

Certified by: _____
Leon R. Glicksman
Professor of Building Technology and Mechanical Engineering
Thesis Supervisor

Accepted by: _____
Adèle Naudé Santos
Chair, Committee on Graduate Students
Acting Head, Department of Architecture
Dean, School of Architecture

Thesis Committee:

Leon Glicksman, Professor of Building Technology and Mechanical Engineering
Thesis Advisor

Leslie Norford, Professor of Building Technology

John Fernandez, Assistant Professor of Building Technology

Richard de Neufville, Professor of Engineering Systems and of Civil and Environmental
Engineering

Flexibility in Building Design:
A Real Options Approach and Valuation Methodology to Address Risk

by

Lara V. Greden

Submitted to the Department of Architecture on April 29, 2005
in Partial Fulfillment of the Requirements for the Degree of
Doctor of Philosophy in Architecture: Building Technology

ABSTRACT

This research develops an approach to designing and valuing flexible systems subject to identified future uncertainties. The approach addresses two shortcomings of current design and decision-making practices that are particularly evident in the buildings industry: 1) systems are designed as though they will remain as static entities despite existing in uncertain environments, and 2) typical decision-making methods, such as net present value and life-cycle costing, do not recognize uncertainty and the ability to make decisions in the future as uncertainties are resolved. The flexible design approach produces an improved design result by addressing the risks and opportunities induced by uncertainty.

Two applications relevant to sustainable building design are developed to demonstrate the approach. First, the value of the flexibility to change the use of a space, thereby increasing building longevity and reducing waste, is evaluated. Option value is defined as the savings of low renovations costs as compared to the cost of renting space on the market. Uncertainties include the market price of rent, timing, amount of space needed, and number of renovations. It is shown that higher upfront investment leading to reduced cost for future change is economically justified in certain scenarios. The value of flexibility increases with increased time horizon and increased uncertainty in the market price of rent. The Black-Scholes formula can be used to approximate the value of flexibility in some cases.

Second, the risk of employing an innovative technology is addressed with a flexible design that provides a fallback position. Specifically, the risk that a naturally ventilated (NV) building becomes overheated in the future due to climate uncertainty is addressed with an option to install mechanical cooling (MC). A model that simulates the system's technical performance under uncertainty demonstrates the value of the option. It is shown that in some locations, increased climate variability does not reduce the viability of NV (i.e., the option to install MC remains unexercised). The likelihood of installing MC is sensitive to design parameters. The results also demonstrate the benefits of the flexible, NV building as compared to MC: delayed or avoided capital costs (e.g., chillers) and cooling energy savings.

Thesis Supervisor: Leon R. Glicksman

Title: Professor of Building Technology and Mechanical Engineering

BIOGRAPHICAL NOTE

Lara Greden received her undergraduate degree in Mechanical Engineering from the University of Minnesota. She has Master of Science degrees in Technology & Policy and Civil & Environmental Engineering from MIT. Her work in sustainable design includes renewable energy systems for housing and rural community center projects in Turkey (with Professor Jan Wampler) and energy modeling for the China Workshops lead by the Building Technology group. Her policy work includes research on the market potential for sustainable residential buildings in China and consulting projects for the Department of Energy while working at Arthur D. Little/Navigant Consulting, Inc. She is a National Science Foundation Fellow, MIT Presidential Fellow, and MIT Martin Fellow for Sustainability.

ACKNOWLEDGEMENTS

I thank my advisor, Leon Glicksman, for providing sound, constructive, and positive guidance throughout this research endeavor. I also thank my entire committee, Richard de Neufville, John Fernandez, and Leslie Norford, for their intuitive, insightful, and constructive manners of advising. I am also extremely grateful to Gabriel Lopez-Betanzos for working with me to develop the NVOV program, as his dedication in seeing the project through was instrumental to the success of the project.

Many people provided valuable input to the research. Thank you to Brad Wolf, Donald Russell, and Bernard Simmons for their enthusiastic cooperation in undertaking the case study on flexible space. Thank you to Professor Jennergren for his assistance in implementing the closed-form solution that validated the flexibility in space-use model. Thank you to Chris Forest for advising me in the process of learning about stochastic climate models and for providing climate change data. I also thank all who provided feedback on the concept of options-based design for natural ventilation, including Jeff Huang, Walt Henry, and Bob Cunkelman. Finally, I thank my classmates and officemates with whom I have had many influential discussions that guided this research.

I am grateful for the sponsorship of the Cambridge-MIT Institute, BP Inc., the National Science Foundation Fellowship, MIT Presidential Fellowship, and the MIT Martin Family Fellowship for Sustainability.

I dedicate this thesis to my husband, family, and friends, and I thank them dearly for their inspiration.

TABLE OF CONTENTS

1. INTRODUCTION.....	15
1.1. MOTIVATION.....	17
1.2. RELATIONSHIP BETWEEN FLEXIBLE DESIGN AND SUSTAINABILITY.....	18
1.3. HYPOTHESIS.....	22
1.4. CONTRIBUTIONS	22
1.5. ORGANIZATION OF THESIS	23
2. LITERATURE REVIEW	25
2.1. RISK RELATED BARRIERS TO ADOPTING SUSTAINABLE, INNOVATIVE ARCHITECTURAL DESIGNS	25
2.2. EXAMPLES OF FLEXIBILITY IN BUILDINGS	29
2.3. OBJECTIVE OF PROJECT EVALUATIONS.....	32
2.4. CURRENT PRACTICE FOR PROJECT EVALUATION - DCF.....	32
2.5. DECISION ANALYSIS (DA).....	35
2.6. REAL OPTIONS (RO).....	36
2.6.1. <i>Financial options</i>	37
2.6.2. <i>Stochastic processes</i>	43
2.6.3. <i>Real options developments</i>	46
2.7. REVIEW OF PROJECT EVALUATION RESEARCH FOR BUILDINGS	49
2.8. CHAPTER CONCLUSION	53
3. A REAL OPTIONS BASED APPROACH FOR ARCHITECTURAL AND ENGINEERING DESIGN	55
3.1. THE CASE FOR DESIGN AS A FACILITATOR OF UNCERTAINTY MANAGEMENT	58
3.2. IDENTIFY UNCERTAINTIES AND SUBSEQUENT RISKS	59
3.3. DEFINE FLEXIBILITY.....	65
3.4. DESIGN AND EVALUATE WITH A ROS MODEL	67
3.4.1. <i>Design</i>	67
3.4.2. <i>Evaluate with real options</i>	68
3.5. USE OF RESULTS IN DECISION-MAKING.....	71
3.6. TRANSFER AND MANAGE	74
3.7. CHAPTER CONCLUSION	75
4. FLEXIBILITY IN SPACE-USE.....	77
4.1. IDENTIFY UNCERTAINTIES AND DEFINE FLEXIBILITY	78
4.2. DEVELOPMENT OF ROS MODEL.....	78
4.3. MODEL DESCRIPTION – BINOMIAL LATTICE WITH SIMULATION	81
4.3.1. <i>Base case model</i>	82
4.3.2. <i>Uncertainty in amount of space</i>	86
4.3.3. <i>Possibility of reversion</i>	87
4.3.4. <i>Two-period (compound option value)</i>	89
4.4. RESULTS	91
4.4.1. <i>Validation of base case</i>	91
4.4.2. <i>Base case</i>	93

4.4.3.	<i>Black-Scholes formula approximated result</i>	99
4.4.4.	<i>Uncertainty in amount of space</i>	102
4.4.5.	<i>Possibility of reversion</i>	109
4.4.6.	<i>Two-period (compound option value)</i>	112
4.5.	DISCUSSION ON USE OF RESULTS FOR DECISION-MAKING.....	116
4.6.	CHAPTER CONCLUSION.....	120
5.	FLEXIBILITY AS AN IMPLEMENTATION STRATEGY: NATURAL VENTILATION	123
5.1.	IDENTIFY UNCERTAINTIES.....	126
5.1.1.	<i>Hybrid cooling strategy</i>	129
5.2.	DEFINE FLEXIBILITY.....	129
5.2.1.	<i>Conceptual design typology</i>	130
5.2.2.	<i>Taxonomy</i>	132
5.2.3.	<i>Components of option value</i>	132
5.3.	DEVELOPMENT OF SIMULATION TYPE ROOS MODEL (EQUATIONS).....	135
5.3.1.	<i>Generalized calculation of option value</i>	140
5.4.	NVOV MODEL DESCRIPTION.....	141
5.4.1.	<i>Stochastic weather generator with climate change</i>	143
5.4.2.	<i>Building energy simulation model</i>	147
5.4.3.	<i>Real options exercise rule</i>	150
5.4.4.	<i>Running the model</i>	153
5.4.5.	<i>Estimation of exercise costs</i>	155
5.5.	INPUT ASSUMPTIONS.....	156
5.5.1.	<i>Office building description</i>	157
5.5.2.	<i>Location(s)</i>	161
5.5.3.	<i>Inputs varied in simulations</i>	162
5.6.	VALIDATION.....	165
5.7.	RESULTS.....	165
5.7.1.	<i>Interpreting the results – Minneapolis</i>	166
5.7.2.	<i>Comparison across locations</i>	174
5.7.3.	<i>Seattle, WA</i>	178
5.7.4.	<i>San Francisco, CA</i>	181
5.7.5.	<i>Chicago, IL</i>	183
5.7.6.	<i>Minneapolis, MN</i>	186
5.7.7.	<i>Effect of increased daily temperature standard deviation</i>	188
5.7.8.	<i>Increase NV air change rate</i>	190
5.8.	SENSITIVITY ANALYSIS OF COOLING ENERGY SAVINGS’ CONTRIBUTION TO OPTION VALUE.....	192
5.9.	SENSITIVITY ANALYSIS OF DELAYED COSTS’ CONTRIBUTION TO OPTION VALUE.....	194
5.10.	IMPACT OF STOCHASTIC ELECTRICITY PRICES.....	198
5.11.	DISCUSSION ON USE OF RESULTS.....	204
5.12.	CHAPTER CONCLUSION.....	206
6.	DISCUSSION AND FUTURE WORK	209
6.1.1.	<i>Create compound models</i>	210

6.1.2.	<i>Explore design issues</i>	211
6.1.3.	<i>Data on cost estimates and conversions</i>	212
6.1.4.	<i>Assess sustainability impacts with life cycle analysis</i>	213
7.	CONCLUSION	215
8.	REFERENCES	223
APPENDIX A. HYBRID BINOMIAL-LATTICE SIMULATION MODEL FOR VALUE OF FLEXIBILITY IN SPACE-USE		233
A.1	"RESULTS".....	234
A.2	"EVENT TREE"	235
A.2.1.	<i>Input parameters</i>	235
A.2.2.	<i>Calculated parameters</i>	235
A.3.3.	<i>Event tree calculation</i>	236
A.3	"OPTION TREE"	236
A.3.1.	<i>Input parameters</i>	236
A.3.2.	<i>Calculated parameters</i>	237
A.3.3.	<i>Option value calculation</i>	237
APPENDIX B. UNCERTAINTY IN AMOUNT OF SPACE MODEL LOGIC		239
APPENDIX C. TWO-TIME PERIOD MODEL LOGIC		241
APPENDIX D: OTHER STOCHASTIC WEATHER GENERATOR POSSIBILITIES CONSIDERED		243
APPENDIX E. SAMPLE RESULTS OF NVOV SENSITIVITY TO COP, P_{ELEC}, AND R		247
APPENDIX F. WHY MODELED HEATING ENERGY CONSUMPTION IS GREATER WITH NV THAN WITH MC		249
APPENDIX G. NVOV USER INTERFACE		253
APPENDIX H. VALUES FOR α AND Δ_0		255
APPENDIX I. LITERATURE REVIEW OF STOCHASTIC ELECTRICITY PRICING MODELS		257

1. Introduction

Sustainable, or green, buildings are at the very early stages of adoption. Their multiple benefits, including improvements in occupant health, productivity, operating costs, quality, and corporate image, motivate their uptake (Fisk, 2000; Bordass et al., 2001; Wilson et al., 1998; Loftness et al., 2001). Figure 1 provides several of the guiding pieces of literature in the field of sustainable design and sustainable buildings. The first is the book *Cradle-to-Cradle: Remaking the way we make things*, co-authored by architect William McDonough and chemist William Braungart, leaders in the movement towards sustainable design. The second is the LEEDs (Leadership for Energy and Environmental Design) certification system, administered by the U.S. Green Building Council, which is becoming a requirement for new buildings in the environmental policies of some firms and institutions in the U.S, including MIT. The third is the book *Green Development*, published by the Rocky Mountain Institute with the intent of providing a comprehensive guide and original collection of case studies. The book is directed towards decision-makers as it illustrates that developing properties within the bounds of respect for the environment is good business-practice. Action and learning, the necessary combination for change, are occurring and give reason for being optimistic about a future where all buildings contribute to sustainability goals.

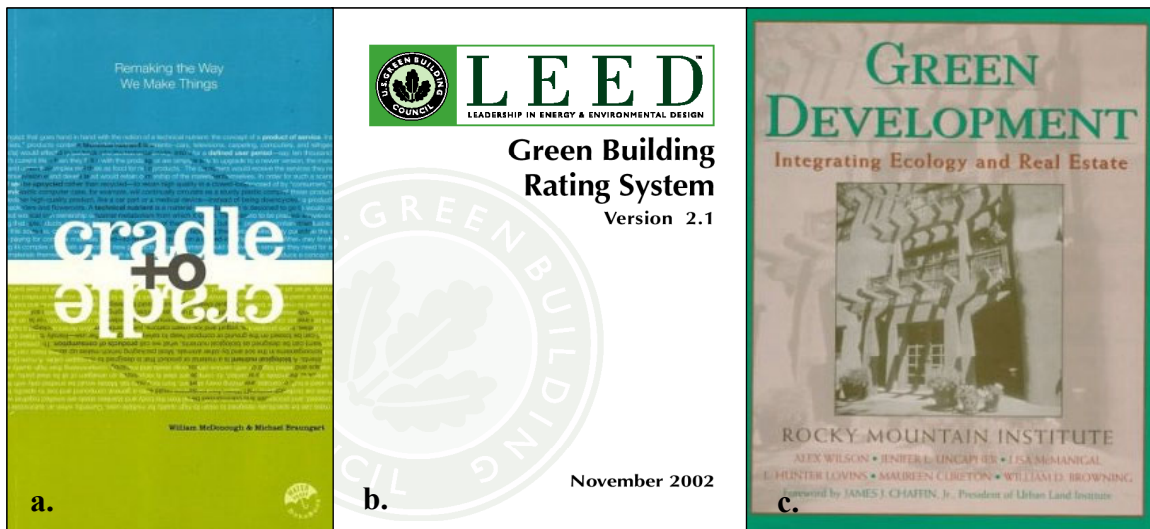


Figure 1. Published evidence of sustainable design in practice. a. (McDonough and Braungart, 2002), b. (USGBC, 2002), c. (Wilson et al., 1998).

Still, change is not occurring at a reasonable rate, as is apparent to anybody suffering from sick building syndrome, living in substandard housing, or, on the positive side, fortunate enough to have experienced the benefits of sustainable building design. Part of the problem lies in the longevity of the existing building stock¹ and its limited, costly ability to adapt. Although examples of adaptive reuse of buildings are easily found throughout history, including the Hagia Sophia in Istanbul, Turkey that served as a church for 916 years, a mosque for 481 years, and as a museum since 1935 (City Guide, 2002), buildings are generally not designed and constructed to absorb change easily. The founding premise of a research group in MIT's Department of Architecture, House_n, which studies and develops dynamic, evolving places, is that

*Change is accelerating, but the places we create are
largely static and unresponsive.*

To bring about necessary change in building typology, new ways of valuing and understanding the evolution of a building throughout its life are needed. A better understanding of the value of flexibility, or the ability to change, will help support strategies that a) reduce the risk of high costs of change, both financial and material, and b) reduce the risk in adopting new technologies. Additionally, flexible designs position a project to benefit from upside opportunity, allowing a manager to take a dynamic approach to decision making as uncertainties evolve. This research aims to develop a formal method for valuation of *flexibility* in architectural design, and the methods and findings are equally applicable to engineering design. The methodology developed and verified in this research will help reveal and explain how risks and opportunities can be addressed through flexible design of buildings, their systems, and engineering systems in general. The results are aimed at the team of decision-makers active in the very early stages of project inception, including architects, engineers, and investors.

1.1. Motivation

Despite widespread acknowledgment that buildings change, they are still designed with a static set of constraints. “Design days” are used to specify heating and cooling systems, which often results in non-optimal, oversized systems. Near-term expected needs largely determine the set of functional requirements that guide space design, without regard for the imminent likelihood of future renovations. Part of the resistance to adopting long-term planning processes arises from perceptions of intense effort, of irrelevance to short-term investors and/or the first set of owners, and that future uncertainty is unquantifiable and, thus, uneconomical to consider. These elements of resistance can be summarized as first-cost and risk-related barriers. However, recognition of the dynamic qualities of buildings at the design phase offers investors the opportunity to reduce their exposure to downside outcomes and increase their ability to benefit under favorable conditions.

Renewable energy systems and energy efficient building design are two classes of technologies with first-cost and risk-related barriers (Davis, 2001; Wilson et al., 1998). Furthermore, the disjointed nature of the building industry means that conservative, traditional practices are rewarded, as no single player is willing to take on the risks alone (FCC, 1996). Currently, decisions on whether or not to invest in a green building are typically based only on first costs and, in some cases, a discounted value of lowered energy and water costs (Kats et al., 2003). Thus, many otherwise superior, innovative technologies are not used in practice due to increased first costs and/or increased risk with insufficient return to warrant investment. In many cases it is simply the perception of these barriers that prohibits consideration of technological innovation.

Discounted cash flow (DCF) analysis (e.g., life cycle costing (LCC) techniques), while an improvement on the building industry’s common practice of first-cost based decision-making, generally uses expected values of input parameters. When the input parameters are, in reality, uncertain and when the performance of the system is a non-linear function of those uncertain variables, expected value based analysis does not capture the range of

¹ In the U.S., the 420,000 commercial buildings (>4.6 billion square feet) constructed in the 1990s represented less than 10 percent of both buildings and floor space in the total 1995 buildings stock

performance possibilities. Thus, DCF and LCC, when based on average assumptions, do not provide information that addresses the risk concerns of project investors.

Formal identification of uncertainties that impact a system's performance leads to two developments: a) systems can be designed with a phased or flexible approach so that managers can steer the system towards opportunities while protecting it from downside events, and b) the performance of the system can be evaluated subject to full distributions of uncertain variables, thereby providing information on the design's potential to reap benefits while avoiding states of poor performance. Thus, a flexible design and valuation approach may provide a method that improves the risk-reward profile of a building or engineering system design.

The full probability distribution of operating performance provides investors with a better understanding of the project's risk-reward profile. Furthermore, identification of the fundamental uncertain parameters that contribute to a system's range of outcomes provides engineers and architects with a tool to design the system with "options." An option-based design will have a different risk-reward profile than an inflexible system, and thus may be more attractive to investors. Options in technical systems provide managers with the ability to take a technological action in the future to steer the system's performance towards opportunities while avoiding poor conditions (de Neufville et al., 2005). Thus, this research is motivated by the premise that flexible, option-based design will help to advance sustainability goals by specifically addressing future uncertainty at the design stage.

1.2. Relationship between flexible design and sustainability

Common architectural terms that conjure an association with the word *flexibility* include modularity, adaptive re-use, renovation, dual-use, and churn. As evidenced in the book *How Buildings Learn*, by Stewart Brand (1994), any individual building will go through many forms of existence in its life, will require replacement parts to keep it fine-tuned, and will consume a non-insignificant amount of resources along the way. A building's

(Diamond, 2001).

inextricable relationship with people – as users, observers, designers, and operators – means that its evolving fate is amenable to unpredictable whims, inefficiencies, and, on the upside, visions. In the latter lies the potential of flexibility, as a design goal and operational mandate, to make a major impact on the sustainable attributes of a building.

A sustainable building, or more generally, a sustainable product is one that exhibits a positive environmental, health, and safety performance record, thereby providing people and the earth, including all of its ecosystems and life forms, with the capacity to thrive in future generations. By the nature of human existence, the definition of a sustainable product also includes economic benefits that outweigh its tangible *and intangible* costs so as to provide financial capital for continued development. Many definitions of sustainability exist, and for the purposes of this research, it is only necessary to provide a definition that sets the context. Discussion of the shortcomings, or outright failures, of current economic and political systems with regards to recognizing full costs and benefits of products and services is beyond the scope of this research. Rather, the definition of a sustainable product as succinctly defined above is used as the starting point to develop a few specific cases for which flexible design and operation, situated under the umbrella of sustainability goals, are shown to be advantageous from a financial standpoint.

Peeling off a layer of the definition of sustainability reveals specific qualities of a product that determine its sustainable performance. Energy consumption, and its related emissions and security issues, is one of the foremost topics discussed upon opening a discussion on improving a product's sustainability. Materials usage, from raw material inputs to consumables required for a product's operational lifetime, is another important category of sustainability focus. The health and safety of people involved in a product's lifetime is a third category of sustainability. Acknowledging the full lifecycle of a product, from cradle-to-grave, or cradle-to-*cradle* as in the book with the same title by McDonough and Braungart (2002), is captured by the concept of flexible design. For buildings, life-cycle costing techniques and (re)commissioning of a building's service systems are two examples of recognizing the importance of a building's on-going, long-term performance. These approaches currently advocated as activities that improve the

sustainability of a building. It is apparent that a whole-life approach to building or product design, by putting on goggles that see past the blue-prints and infancy stage, is one way to contribute to sustainability goals. Design for flexibility fundamentally embodies a life-cycle approach to design.

One tangible sustainability benefit of flexible design can be seen when the flexibility is in the use or configuration of a space. In Australia, where offices typical undergo a new interior fitout every three years, up to 32 percent of all waste going to landfill is from the churn of fitouts and refurbishments (GBCA, 2004). Thus, the Green Building Council of Australia's 'Green Star- Office Interiors' rating tool includes items that address recycle and reuse for office fitouts. As another example, the State of Minnesota's Sustainable Building Guidelines (MSBG) include the following implementation note in the 'Materials and Waste' section: "in predesign-programming, estimate the percentage of building materials that are likely to be affected by the average churn rate for the agency or project type, and set goals for integrating flexibility and adaptability into the design of primary material resource areas most impacted by churn" (MSBG, 2003). These anecdotal examples of the potential for flexible design to reduce material waste as a building adapts, although few, provide solid evidence of positive environmental potential.

Another example of the potential for flexible design to meet sustainability goals is in the system or related benefits that it may create. For example, under floor air-distribution systems with relocatable diffusers are identified by Loftness and Mathews (1999) as a design strategy for enabling reconfiguration of a space. These systems have a related benefit in that under floor air-distribution is a more effective way of providing conditioned air to occupants and results in lower energy consumption. As another example, task lighting and daylighting strategies also improve the configuration flexibility of a space while providing energy and occupant satisfaction benefits (Loftness and Mathews, 1999). These examples show how flexible and sustainable design, although not inherently indicative of the other, can be complimentary.

There is yet another way that design for flexibility can benefit sustainability – it can be used to address risk. In real estate, leased-space is congruent with flexibility in that real estate managers are not locked into an asset indefinitely, thereby reducing the future risk of paying rent for unnecessary space or of paying a higher than current market level of rent. The concept of flexibility to reduce risk in the design of a system is analogous to the “flexible” lease. Computers and other information technologies are the shining examples of flexibility. One laptop user may desire two batteries while another wants one battery and one CD-DVD ROM. Flexible design of ports allows both customers to be satisfied with a single laptop base design that accepts modules of batteries, CD-DVD ROM’s, etc. Design for modularity is a hallmark of the computer industry (Baldwin and Clark, 2001). The same concept can be applied to product design with the specific objective of reducing the risk that the product will not perform as needed so as to succeed in competitive markets while at the same time be positioned to take advantage of potential opportunities if and when they evolve. It is evident that flexible design is a start, and that proper management of the flexibility with the help of a decision-support ‘radar screen’ is necessary to realize benefits. This work explores two cases of the value in design for flexibility: adaptable space and hedging the risk that an innovative, sustainable technology fails.

Before moving into flexible product design for buildings, it is noteworthy that design for flexibility does not suffice to address all goals for sustainability. In particular, flexibility cannot address health risks to the extent that realization of a poor health outcome occurs over an extended time-frame, likely much too long for activation of a flexible capability to remedy the situation. Furthermore, it is difficult to link health problems to specific causalities. Thus, flexibility’s contribution to sustainability goals lies in reducing waste and/or positioning a product/design/or system with sustainability benefits to hedge financial risk and, on the upside, to take advantage of evolving opportunities.

1.3. Hypothesis

The hypothesis in this thesis, tested through proof by demonstration case studies, is that a flexible design strategy, one that addresses uncertainties in future performance, can hedge losses, provide opportunities, and therefore result in an improved investment, as compared to a static design. Furthermore, a real options valuation methodology provides valuable insights to decision-makers concerned about the uncertainties, and thus risk, associated with innovative designs and technologies.

This research aims to develop an approach that embraces uncertainty as a guide to the design and economic evaluation of a building, engineering system, or other object of design. By addressing uncertainty through flexible design features, ones that allow managers to take action in the future as uncertainty is resolved, the resulting design will exhibit improved performance, financially and according to other desired metrics. This premise is particularly relevant to sustainable buildings because of the risk associated with new technologies, uncertain climate, and market acceptance. Furthermore, the degree of success of many sustainable building features, such as energy efficient designs, depends nonlinearly on uncertain variables.

At this point in time, too few examples of buildings designed with well-defined elements of flexibility exist to provide empirical evidence. Thus, models are needed to evaluate a building's performance when designed with flexibility. Results from these models can be used to inform decisions to invest in flexibility. In the future, as more building projects with elements of flexibility are constructed, the original hypothesis may be tested with actual data.

1.4. Contributions

The major contribution of this research is development of a generalized, flexible design approach for architectural and engineering systems, including a valuation methodology to support investment in flexibility. Two applications for flexible design, and appropriate valuation models for each, are developed to demonstrate the potential of the methodology. The framework, models, and results address an audience with interest in

advanced strategies for managing a system via technical means of flexibility, including designers, developers, building owners, and building managers.

The first is a study of the value of a space designed with the flexibility to be changed to a new use in the future. The real options valuation model, based on a combined binomial lattice and simulation technique, demonstrates the tradeoff between initial investment in flexibility and future costs of renovation. Guidelines are given for applying the Black-Scholes formula to obtain initial estimates as to the value of flexibility relative to rental price.

The second study addresses flexible design as an implementation strategy for an innovative technology. The case for natural ventilation to be implemented with the option to install mechanical cooling in the future, if the risk of overheating is realized, is demonstrated through a model that simulates the building's thermal performance under climate uncertainty. The results demonstrate the shift of capital cost obligations and the potential for increased energy savings from the flexible approach as compared to a standard mechanically cooled building. It is shown that in some climates, increased variability in climate does not reduce the potential of NV to be effective, and recommendations are made for important design parameters and for variable comfort standards.

1.5. Organization of thesis

The thesis is organized as follows. Chapter 2 presents the literature review. Topics covered include barriers to adopting sustainable building technologies, current practice for real estate project evaluation, flexibility in buildings, and valuation theory, including real options theory. Next, in Chapter 3, the approach to flexible design and valuation developed in this research is presented. Chapter 4 presents the case for flexibility in space-use. The option to convert a space to office space under various scenarios is evaluated and general guidelines are deduced. Chapter 5 presents a case for flexible design as an implementation strategy for an innovative technology. The value of the option to install mechanical cooling in a naturally ventilated building to address the risk

that the NV building overheats is evaluated subject to climate uncertainty. Results are presented for various locations and climate assumptions, and major findings are discussed. Chapter 6 provides a unifying discussion and suggestions for future work. Finally, Chapter 7 concludes.

2. Literature Review

The literature review provides evidence of the motivation for this research as well as underlying theories that found the subsequent models.

2.1. Risk related barriers to adopting sustainable, innovative architectural designs

The guiding motivation of this research is to support adoption of sustainable building design practices and technologies. As previously discussed, a unique definition does not exist for a sustainable, or green, building or building technology. The concept embodies efforts to reduce the environmental impact of a building, improve conditions for occupants, and contribute positively to the local area in which it resides. Discrete categories of design and component specification that contain elements that affect a building's level of sustainability include energy performance, controllability of heating, ventilation, and air-conditioning (HVAC), daylighting and views, water consumption, waste-water management, construction and renovation waste, renewable energy, recycled and renewable materials, emission-free materials, transportation implications, and heat island affect (USGBC, 2002). Typical design and construction practices do not address these sustainability relevant categories. Thus, most sustainable designs and technologies are innovative as they are far from a state of widespread use in common practice. There is increased risk in employing sustainable, innovative building technologies and architectural designs for a variety of reasons relating to individual responsibilities held by parties within a building's supply chain.

Real estate development and decisions to use innovative building technologies involve three sets of stakeholders (FCC, 1996):

- The development team consisting of the designer, developer, and construction contractor;
- The tenant and/or owner; and
- The institutional investor (e.g., the bank that provides the mortgage or construction loan).

The barriers to sustainability-related innovation in building design arise from concerns of each stakeholder individually as well as contractual relations among the parties. For the development team, competition creates pressure to keep first costs low. A developer is most likely to make an investment in technical innovation only if it will be visible to the consumer and, therefore, warrant asking for a higher price (OTA, 1992). However, tenants, representing the demand-side of the market, have not yet emerged to demand green building features. Characteristics such as location and functionality of space dominate decisions, and potential savings in energy or operating costs require a very short payback period for initial investment (Greden, 2001). Institutional investors tend to reward conservative practices because of the many sources of risk that enter real estate projects (DOE, 2000). Byrne (1996) identifies four main financial factors that impact an investor's appraisal of development projects:

- short-term borrowing cost,
- building costs,
- rental income, and
- investor's yield.

All of these factors refer to construction, rental price, and financial rates of monetary value, leaving out future uncertainties in health, regulation, environment, energy costs, and the relationships between a building and these “externality” factors. In summary, the fragmented nature of the commercial buildings sector means that individual stakeholders are seldom large enough to risk sizeable investments on their own or to capitalize on any resulting innovations.

The classic “landlord-tenant” problem epitomizes the fragmented nature of commercial real estate development. The landlord, or building owner, is responsible for capital expenditures and thus seeks to minimize those costs, all other things equal. The landlord may recoup some of those costs by increasing the rental price; however, all other factors being equal, an economically rational tenant will look for a rental property with the lowest rental price. This problem is especially apparent in energy-conservation projects. For example, passive building design, higher quality insulation, low-e windows, and energy efficient lighting may cost more as an upfront investment; however, it is generally

the case that the investment pays for itself, in the form of reduced energy costs, well within its lifetime. The disconnect lies between the party that makes the expenditure (i.e., landlord) and that which receives the economic benefit (i.e., tenant). The solution to the landlord-tenant problem, such as described, requires two factors. First, from the landlord's perspective, the cost of energy efficient design should be included in determination of the rental/selling price. Second, prospective renters or buyers need to be provided with information on the energy cost savings of that property (Greden, 2001). Instruments such as the Energy Star mortgage attempt to bridge these two factors formally. When the energy (cost) saving advantages of a design can be verified, an Energy Star mortgage provides a more favorable interest rate reflecting the income that is "freed up" by the reduced energy expenses (Energy Star, 2005).

Donovan (2001) conducted a survey of four tenants and nine developers of office buildings located primarily in the Northeastern U.S. to determine their views on three green building technologies: photovoltaics, underfloor air distribution, and natural ventilation (NV). This small-scale survey suggests that greater value from green building technologies can be realized in four ways:

- reduced operating costs,
- increased sale price upon disposition of property,
- higher than market rent, and
- visibility and publicity for the developer (i.e., branding).

Several barriers are highlighted in the responses to the survey. First, although occupants will generally recognize the cost saving benefits of under floor air-distribution in a standard lease, developers seemed to lack the knowledge that raised access flooring and under floor air-distribution are technologies that can be used not only to reduce utility costs, but also to reduce down time between leases. Second, natural ventilation is seen as a very risky technology. Only one of four tenants and five of nine developers responded that NV was a promising technology. Donovan (2001) notes that, for developers, NV may reduce the capital cost of the project by reducing the amount or size of HVAC equipment needed. Tenants may be less attracted to NV because they fear that it will result in an inadequate system that will not properly condition the space. This is

apparently not offset by the fact that operating expenses would be reduced (Donovan, 2001). The majority of developers in Donovan's survey will wait to "go green" until tenants are willing to pay higher rent or are forced to adopt green practices by building codes. One respondent stated, "In my experience, developers react better if there is a level playing field which means that green buildings will prosper only with regulations forcing all to behave the same way." (Donovan, 2001). This survey of commercial office space stakeholders elucidates the financial risk concerns of developers and quality of space concerns for tenants of using non-traditional, innovative technologies.

The case of NV further illustrates the risks of innovation in buildings on the design side. A study funded by California's Public Interest Energy Research Program (PIER, 2003) concludes that architects and engineers find it difficult to specify innovative cooling strategies, such as NV, partly due to a lack of credible evidence of efficacy and an overall lack of selection and maintenance information. Likewise, a Dutch study found that insufficient mention of NV in design briefs, inadequate ability to control indoor temperature in the summer, and little experience and knowledge with NV explain why offices buildings are not more often designed with this passive cooling strategy (de Gids, 1998). In addition, building designs that utilize new materials and systems require greater attention by the design professional after award of the contract, as success often depends on proper installation. It is likely that the designer will be held accountable for failure even if they do not have the opportunity to monitor the project to completion (FFC, 1996). However, the current trend is towards limited retention contracts for design professionals to oversee the construction and commissioning phases.

Davis (2001) identifies three areas of improvement needed to address the financial risks of sustainable, innovative building technologies. First, there is the need to transfer some of the value of long-term benefits to the development team from the tenants or owners (Davis, 2001). Second, the risk that green products or designs do not perform well inhibits their use as it represents a financial risk for *both* the investor and the development team, without reward being properly attributed to either party. Third, as markets are consumer driven, there is a need for credible evidence of building

performance, environmental effects, fiscal performance, and productivity impact so as to motivate the tenant/owner side to demand innovative buildings (Davis, 2001). The disconnect between risk and reward brings attention to the need for improved understanding of the nature of building technology uncertainties, which may then lead to contracts, warranties, and information sharing to bridge these barriers.

2.2. Examples of flexibility in buildings

Flexibility in buildings can be defined through the characteristics of a building that make it able, on the basis of its physical composition, to adapt or modify itself to changes. The conceptual notion that flexibility has value has been embraced and implemented in several architectural examples. Millennium Laboratories of Cambridge, Massachusetts recently constructed a new laboratory building with maximum flexibility to switch between chemistry and biology labs, depending on business needs. Millennium Laboratories, designed by Elkus-Manfredi Architects, won the *R&D Magazine's* 2003 Award for Laboratory of the Year owing primarily to its flexible design concept (Mallozzi, 2003). A second example is the hybrid electric-steam chiller plant at the University of Maryland's basketball arena. The ability to use either electricity or steam allows the operations manager to manage energy costs (ESM, 2003). The Millennium Laboratories building and the University of Maryland basketball arena are picture in Figure 2.

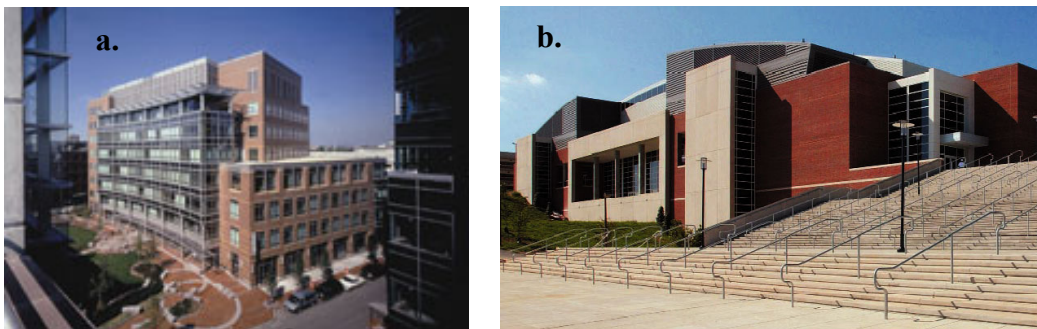


Figure 2. Two examples of flexible design in buildings: a) the Millennium Laboratories building can be switched between chemistry and biology labs (Mallozzi, 2003; Photo by Justin Maconochie), and b) the University of Maryland's basketball arena uses a hybrid electric-steam chiller plant (ESM, 2003).

In another example of flexible building designed, Arrowstreet Architects designed a telecom server building with the option to switch to an office building (Batchelor, 2003). The developer of the project recognized the value in a back-up strategy of being able to sell the building as office space in the event that the market for telecom-server buildings decreased substantially. A fourth example comes from the increasing variety of office building products that accommodate change, including movable walls, tiled carpet, and raised floors, which allow easy access to communications wiring (Kats et al., 2003). These examples illustrate real-world identification of uncertainty and subsequent use of flexible design to address risk.

One of the primary motivations for flexible space design is the need to facilitate less costly, quicker changeovers in space-use (Joroff and Bell, 2001). Key drivers of the occurrence of changeovers, and the need for flexible space, are the rapid pace of changing business needs, mobile employees, and uncertain real estate markets. As suggested by anecdotal evidence, flexible space may also facilitate greater productivity and reduced long-term costs. Another motivation for flexible building systems, particularly for HVAC systems, is the need to manage highly variable cooling loads and fluctuating energy prices (ESM, 2003).

Despite the growing body of examples, intentional design for adaptability is still relatively uncommon in architecture and building system engineering. Fernandez (2002) discusses methodologies for designers to produce a more flexible and responsive building, including scenario-based designs, incorporating a flexibility scenario into the design brief for building requirements, and construction modes that allow for an inconclusive finish to the building. Fernandez (2002) studied and designed a set of buildings intended to contract over a period of several decades, largely due to the identified uncertainty and significant risk in business decline and subsequent lack of need for a corporate building. The design is based on calculation of a portfolio of spaces with differing lifetimes that, on average, equals the expected value of the overall lifetime and square footage needs of the owner/occupier. The resulting building design is composed of three distinct areas of varying lifetimes, composed of office spaces and a materials

reclamation shop. Fernandez (2002) illustrates the disassembly paths and several possible modes of contraction, thus providing a guiding example for adaptable design.

Two of the primary barriers hindering consideration and implementation of more flexible space are higher first-cost and reluctance to depart from traditional, less flexible interior build-outs, such as individual offices. These reasons appear to contradict the common occurrence of renovations at great expense due to structural, HVAC, and interior designs intended for a set of initial specifications. Owner-occupied buildings have the opportunity to actively involve their corporate real estate managers in corporate strategic planning, with the goal of designing the company's physical facilities with reverence for adaptability. According to a survey by Allard and Barber (2003), redesigning the workplace synchronized with a company's ability to make changes successfully in each of the other areas critical for strategy execution. However, without involvement in corporate strategic planning, the corporate real estate manager can only assume a reactive role, which is costly and time consuming (Avis, 1990). The corporate real estate manager will be better able to coordinate facility related needs across business units when formally involved in strategic level planning.

In the real estate sector, the effectiveness of ongoing decision-making is often limited by rigid construction timelines and equally unyielding designs. Typically, buildings are designed to meet near-term, relatively certain needs. However, business needs that originally dictated the design constraints are almost certain to change, sometimes even during the design and construction phase. During these initial phases, changes are possible but result in extra, unanticipated costs. Further on in a building's life, changes are also common, as illustrated by a large construction sector devoted purely to renovations². Change is an evident and inescapable characteristic of the built environment and deserves attention at the initial design phases.

² Over one-third (38%) of U.S. building construction activity is in remodeling and renovation (USDOE 1998a as referenced in Diamond, 2001).

2.3. Objective of project evaluations

The primary objective of project evaluation is to achieve a result useful for decision-making. Such a result will rank project investment choices clearly while maintaining sufficient realism (de Neufville, 1990). No one approach or evaluation technique fits all situations. Differentiating factors of a project lie in its context, and include assumptions about comparability between the elements of an evaluation and the degree of uncertainty in the possible choices. Elements to compare include (de Neufville, 1990):

- objects over time,
- quantities of objects at any single time,
- different objects, and
- preferences of the various decision-makers.

Different objects, and the consequences of those objects, present a difficulty to any analysis. For example, the value of investments in safety, health, and economy are not comparable in an obvious way, and thus should be kept separate (Ashford, 2002). There are three basic approaches to project evaluation from a financial standpoint:

- DCF (including cost-benefit analysis and NPV, where risk is treated in discount rate)
- Decision Analysis (DA) (including probabilistic risk assessment, decision-trees, and utility functions)
- Real Options (RO) (right to make contingent decisions, strategic valuations)

The shortcomings and advantages of DCF analysis include lack of ability to deal largely with uncertainty and ability to provide simplicity, respectively. Conversely, the latter two methodologies - decision analysis (DA) and real options (RO) - provide ways to deal with and manage uncertainty and flexibility in a project.

2.4. Current practice for project evaluation - DCF

Investments in new buildings or infrastructure upgrades typically rely on one of two decision-making methods: first-cost minimization and net present value (NPV) maximization. Other socio-political factors also influence building-related choices, including reputation, environmental responsibility, cost structure design, personal

relationships in the supply chain, and desire to attract or retain people. First-cost minimization is a typical decision-making criterion in many types of decisions, from large construction projects to consumer buying. This method is reinforced in the real estate sector due to the large number of stakeholders in any particular project and a high level of competition. NPV calculations are most often used at the initial stage of project inception to determine whether or not the project deserves investment. NPV based decisions may also be used to assess capital equipment investments that have an operating cost, such as HVAC and renewable energy systems. This is typically called life cycle costing (LCC).

The basic decision rule applied to real estate investments is to invest in the project if the net present value (NPV) is greater than or equal to zero. The NPV is determined with discounted cash flow (DCF) analysis, including adjustments for time and risk (Geltner and Miller, 2001). The general horizon of evaluation is ten years after the initial occupancy date, which is the common length of leases for commercial space. DCF analysis may or may not include operating costs, as it depends on whether the owner or tenant will be contractually responsible for paying for them. Generally, operating costs, and thus any savings from more efficient designs are not considered. Thus, ‘first costs,’ including construction and design, dominate the DCF result.

The DCF procedure consists of three steps (Geltner and Miller, 2001):

1. Forecast the expected future cash flows (CF_t)
2. Ascertain the required total rate of return (r)
3. Discount the cash flows to the present value at the required rate of return.

This is illustrated in Figure 3. Mathematically, these three steps can be summarized by the following equation for the NPV of a series of periodic cash flows (CF_t)

$$NPV = E[CF_1](1+E[r])^{-1} + \dots + E[CF_n](1+E[r])^{-n} \quad (2.1)$$

Where the $E[\bullet]$ designator means the expected, or average, value of a variable. The variable r is the discount rate per period, and n is the total number of periods.

The shortcomings of DCF calculations are threefold. First, the methodology considers a small set of discrete alternatives to fulfill a particular project goal, without the possibility for interactions and feedback into the design of any particular component. While it could be argued that the set of design alternatives covers all possible permutations, the analysis does not give particular information on the benefits of any single attribute. Second, DCF analysis must make an assumption on the discount rate. This highly subjective estimate is likely to change over time with changing market conditions and opportunity costs associated with other internal projects at the firm or agency. Finally, a simple DCF calculation does not include the ability to value a project decision at a future point in time. In summary, DCF is good for calculating discrete projects, with reliable estimates of cost, cash flow, and interest rates (or discount rates), that do not require change or adaptation at some future point in time. Although DCF calculations are useful and appropriate in some situations, it is apparent that dynamic, responsive, and evolutionary building typologies cannot be fully assessed with such a method.

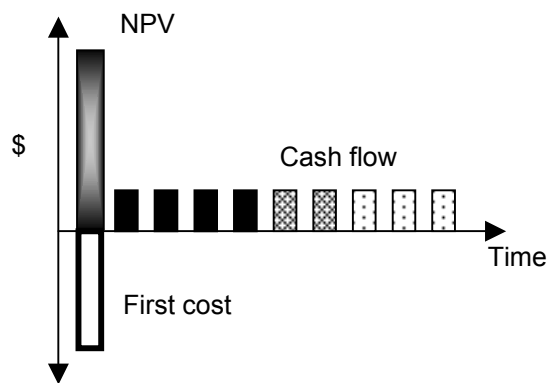


Figure 3. Generalized cash flow scenario for a project illustrates first cost expenditure (capital outlay, investment), operating cash flow (income, energy cost savings), and estimated net present value (NPV) of the project.

2.5. Decision Analysis (DA)

Whereas standard discounted cash flow (DCF) analysis does not have the capability to properly assess project value when the ability to make a future decision is integral to its determination, decision analysis (DA) and real options (RO) techniques bring uncertainty and future decision rules explicitly into the mathematical formulation of project value. Decision analysis is discussed in this section and real options in the following section. Decision analysis (DA) is a method of evaluation that leads to three results (de Neufville, 1990):

- Structuring of a complex problem,
- Definition of the optimal choice for any time period of time (based on joint consideration of the probabilities and natures of outcomes), and
- Identification of an optimal strategy over many periods.

A decision-tree is used to structure the choices, possible outcomes, and the probabilities associated with each outcome. As shown in Figure 4, a decision tree contains a sequence of alternating decision nodes and chance nodes. Decision nodes are the moments when possible courses of action are considered and a decision is made. Chance nodes represent the probabilities that a future outcome will occur in the period(s) after a decision is made. The sum of the probabilities for any chance node is unity. The expected value (EV) for each chance node is determined by

$$EV = \sum P_j O_j \quad (2.2)$$

where P_j is the probability of outcome O_j , which depends on the decision made previous to the chance node. Cost models, which may be based on DCF analysis, are usually constructed to estimate the values of the various outcomes in different states of nature.

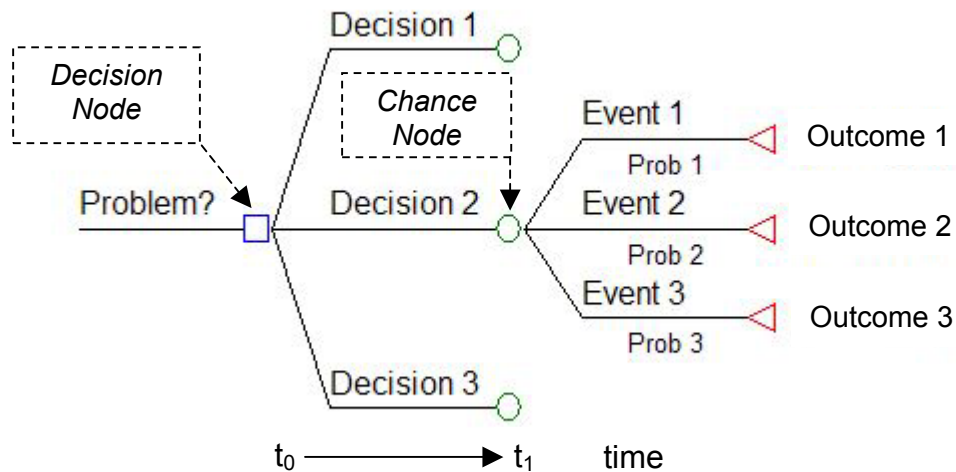


Figure 4. Conceptual structure of a one-stage decision tree, showing the decision-chance-outcome node sequence.

One benefit of structuring the problem as a “tree” or as a set of likely possibilities is that it helps people realize that choices are not polar, but actually include a wide range of combinations. Thus, a decision tree provides both a basis for discussion and the basis for the actual analysis (de Neufville, 1990).

2.6. Real Options (RO)

Real options (RO) theory is based on financial options-pricing theory and the viewpoint that uncertainty can create value. An example of a financial option is an option to buy or sell a stock in the future at a predetermined price, as will be further explained herein. In essence, an option is the right, but not the obligation to take an action in the future. “Options” are analogous to the different courses of action possible at the decision nodes of a decision tree. Options are valuable where uncertainty exists.

In reality, like decision analysis with its “tree” visualization approach, real options is a way of thinking. The major difference between RO and DA is that RO does not require reduction of full probability distributions to a set of discrete probabilities and outcomes

(i.e., P_j and O_j). Real options opens the mindset of decision-makers to think of decisions as contingent upon future knowledge gained about a market or technological performance. Real options concepts implore decision makers to question

- a) how exposure to uncertainty can be reduced, and
- b) how payoffs can be increased if there is a good outcome (Amram and Kulatilaka, 1999).

One quick lesson from the ROs approach is that there is great-value in making phased-investments in large projects in uncertain markets. Whereas this approach may be easily applied in situations marked by a single or few decision maker(s), such as decisions to expand manufacturing capacity or roll-out products in new markets, application to real estate remains elusive due to the fragmented nature of the real estate industry. Examples of common decisions in real estate that demonstrate flexibility as a way of thinking include leasing instead of owning, holding onto a piece of property for future development, use of heating or cooling equipment that can switch between two different types of fuel depending on relative prices, and the ability to change a building's electricity loads so as to respond to real-time signals of electricity prices. Before applying options theory to real, or physical, assets as opposed to financial assets such as stocks, it is useful to review the main financial options concepts and the stochastic mathematical theory that lead to their development.

2.6.1. Financial options

Financial options give the owner the right, but not the obligation, to purchase (or sell) a stock for a prespecified price on or by a certain date (Brealey and Myers, 2000). The date by or which action must be taken is called the exercise date. The price to be paid for the stock on the exercise date is the strike price. On the exercise date, the market value of the stock is compared to the strike price. For a "call" option, as illustrated in Figure 5, the owner will exercise the option to buy the stock if the market price is greater than the strike price. For a "put" option, the owner will exercise the option to sell the stock if the market price is less than the strike price. The value of an option depends on the payoffs to the contingent exercise decision, the length of time to the exercise date, and the

volatility of the stock price, which is called the underlying asset (Amram and Kulatilaka, 1999).

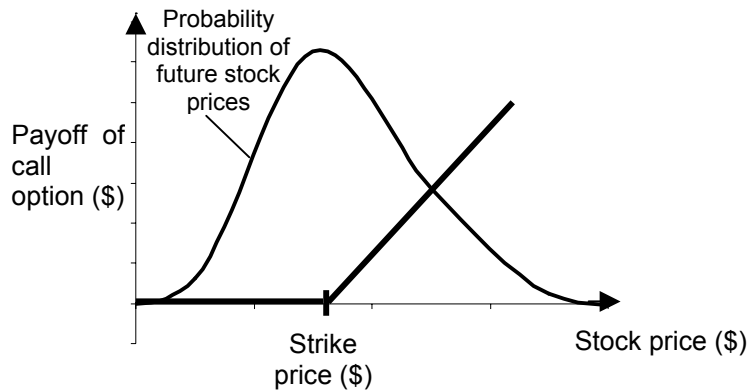


Figure 5. Payoff of a call option, with illustration of the probability distribution of possible future stock prices.

Options are valuable precisely because of uncertainty. This is illustrated by the probability distribution of future stock prices in Figure 5. Stock option value, or the price paid to hold a stock option, increases as uncertainty increases. With an option, the owner is protected from downside outcomes, yet stands to gain from upside realizations of stock price. Models to determine financial option value generally begin by assuming that future stock price movements are a random walk, which is also termed geometric Brownian motion (GBM). Partial differential equation solutions and binomial lattices are used to price financial options subject to several important simplifying assumptions.

The primary assumptions used to establish the mathematical methods for pricing financial options are geometric Brownian motion, constant volatility of the stock price, existence of a complete market where arbitrage is non-existent, and complete liquidity of the underlying asset (i.e., stock). The no-arbitrage postulate describes a situation in which all investors have complete information and thus the market price of the asset is the only price for which any and all buyers will pay. The complete liquidity assumption

implies that the asset can be freely bought or sold in any quantity at any time. The failure of this last assumption to hold in real-world markets brought about a major crash in options trading in the late 1990's, when Long Term Capital Management, Inc. was not able to buy the large quantity of assets needed to hedge its options positions (Dunbar, 2000). The GBM assumption describes how the price of a stock moves. Another possibility analyzed in the research literature is that of a jump process, which describes sudden movements in stock price not captured by a random walk process. A numerical value of volatility, or standard deviation, of stock price is used to describe GBM, and for modeling simplicity this value is assumed to be constant over time. Historical stock price data can be used to determine volatility, but choices must be made on the time frame over which volatility is calculated. Given these assumptions, a replicating portfolio is used to establish a risk-free preference between a) holding a call option and b) holding a certain quantity of the underlying asset financed by selling risk-free bonds. The payoffs to the portfolio are theoretically risk-free, and thus the risk-free rate of return is used to value the option.

An example construction of a replicating portfolio is given to illustrate how an option is priced using this concept and how the exact same returns to an option may be yielded by instead holding a portfolio of risk-free loan and the stock. No calculations such as this will be made later in the thesis, but it is useful to have a fundamental understanding of the mechanics of a replicating portfolio so as to relate options pricing assumptions to concrete calculations. Furthermore, derivation of the risk neutral-probability (q), a parameter that will be used in the Flexibility in Space-Use models, is based on the concepts of a replicating portfolio. Begin by assuming that the value, or price, of a stock follows a discrete time random walk in which it may either move "up" or "down" in any time interval. In this example, assume that the current stock price S is \$41 and the one-year possible future prices are either \$59.95 (up) or \$32.90 (down) (based on McDonald, 2003). We want to price a call option with a strike price K of \$40, slightly less than the current stock price of \$41, expiring one year from now. The risk-free rate of return, generally given by U.S. Treasury bills of similar maturity to the option lifetime, is assumed to be 8 percent.

Figure 6 shows a binomial representation of the stock price at the current time and one year from now; the value of the call option at the current time and one year from now; and the amount of the loan to finance the long position (i.e., owning) in the stock. The first step to pricing the option is to construct a table of payoffs of the portfolio (Table 1). The value of the stock in the *down* state is used to determine the size of the loan payoff one year from the present. The value of the portfolio one year from now is \$27.05 in the up state and \$0 in the down state; you have hedged your position because nothing can be lost, but something might be gained.

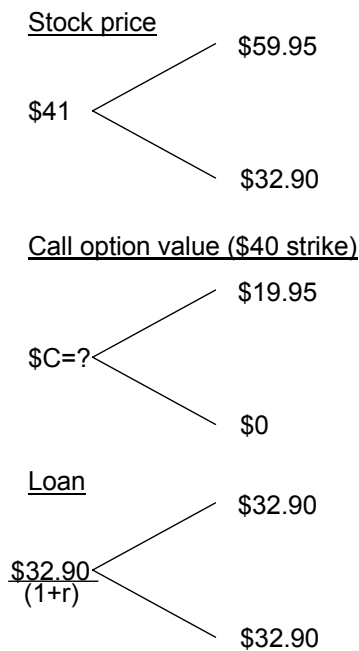


Figure 6. Replicating portfolio example.

Next, the value of the call option C , as shown in Table 2, is determined for each of the up and down states:

$$C_u = \max [S_u - K, 0] = \max [(\$59.95 - \$40), 0] = \$19.95 \quad (2.3)$$

$$C_d = \max [S_d - K, 0] = \max [(\$32.90 - \$40), 0] = \$0 \quad (2.4)$$

Notice that the value of the option in the down state is also \$0, just like the hedged position of the replicating portfolio. To price the call option, which represents only a fraction of the portfolio, the ratio δ is calculated

$$\begin{aligned} \delta &= C_u / P_u \\ &= \$19.95 / \$27.05 = 0.7375 \end{aligned} \quad (2.5)$$

where C_u is the value of the option in the up state and P_u is the value of the portfolio in the up state. To determine the value of the option C , this fraction δ is multiplied by the time zero value of the portfolio P_0 :

$$\begin{aligned} C &= \delta P_0 \\ &= 0.7375(\$10.54) = \$7.77 \end{aligned} \quad (2.6)$$

The calculation shows that an option with strike price of \$40 expiring one year from now on the stock specified (price of \$41 today and either \$59.95 or \$32.90 one year from now) is worth \$7.77 to a risk-neutral investor (i.e., one who is concerned with expected payouts).

Table 1. Portfolio Costs and Payoffs

	t=0	t=1	
	Start	<i>End up</i>	<i>End down</i>
Stock price	41	59.95	32.90
Buy stock (t=0), Sell stock (t=1)	-41	59.95	32.90
Receive loan (t=0) Pay back loan (8%) (t=1)	30.46	-32.90	-32.90
Net portfolio position	-10.54	27.05	0

Table 2. Value of Option Using Replicating Portfolio Method

	t=0	t=1	
	Start	<i>End up</i>	<i>End down</i>
Stock price	41	59.95	32.90
Buy 1 Call (t=0), Exercise result (t=1)	-C	19.95 (=MAX[59.95-40, 0])	0 (=MAX[32.90-40, 0])
Balancing fraction δ of net portfolio position	-7.77 =(0.7375)(-10.54)	-19.95 =(0.7375)(27.05)	0 =(0.7375)(0)
Net	C=7.77	0	0

The portfolio position exactly protected the owner from the downside in stock prices, as did the call option. In the financial markets, positions in replicating portfolios are made to hedge option holdings as well as to make risk-free “arbitrage” profits when mis-priced options are discovered. This example demonstrated the basics of call option pricing using the assumptions of a discrete random walk, constant volatility of the stock price, existence of a complete market where arbitrage is non-existent, complete liquidity of the stock, and access to risk-free loans. These assumptions are not perfect for financial options or for “real” options. Thus, it is not necessarily appropriate to use financial options models to value real options.

2.6.2. Stochastic processes

The objective in presenting this discussion is to provide an understanding of the underlying mathematics of options theory, including geometric Brownian motion, as a foundation for applying the concepts of flexibility and risk management to decision-making and valuation for buildings (systems, design, technologies). Professors Robert Merton, Fischer Black, and Myron Scholes developed stock option pricing theory in the early 1970's (Black and Scholes, 1973; Merton, 1973). Merton and Scholes were awarded the Nobel Prize in Economic Sciences in 1997 for their work, which helped to revolutionize risk management in financial markets:

Robert C. Merton and Myron S. Scholes have, in collaboration with the late Fischer Black, developed a pioneering formula for the valuation of stock options. Their methodology has paved the way for economic valuations in many areas. It has also generated new types of financial instruments and facilitated more efficient risk management in society.

-October 14, 1997, Press Release: The Sveriges Riksbank (Bank of Sweden) Prize in Economic Sciences in Memory of Alfred Nobel for 1997

The mathematics of options pricing theory is based on stochastic processes, as presented in this section. The following discussion is based largely on “Stochastic Processes and Ito’s Lemma,” Chapter 3 in *Investment under Uncertainty* by Dixit and Pindyck (1994).

A stochastic process is a variable that evolves over time in a way that is at least in part random (e.g., next week’s temperature or a company’s stock price). A stationary stochastic process has statistical properties that are constant over long periods of time where as a nonstationary process may grow (or decline) without bound. Temperature is a (relatively) stationary process and stock price is a (lognormal) nonstationary process. A mean-reverting, or first-order autoregressive, process is a stationary process in which the variable tends to revert back to its long-run expected value.

A Wiener process, also called Brownian motion, is the primary class of stochastic processes of interest to options valuation discussion. Geometric Brownian motion will be described later. The Scottish scientist Robert Brown observed what is now termed “Brownian motion” through a microscope in 1827, watching dust particles collide as they made random movements in any direction. A Wiener process is the mathematical equation for Brownian motion, or the continuous limit of a discrete-time random walk. A random walk can be conceptualized by this thought experiment (Jeans, 1959): traveling at random, a person must take four times as many steps along an axis to travel two miles as to travel one mile. The average distance advanced increases only as the square root of time, and the sample paths of Brownian motion have a very jagged appearance with many ups and downs (Dixit and Pindyck, 1994).

The Wiener process can be used to model an extremely broad range of variables that vary continuously and stochastically through time. The Wiener process is a continuous-time stochastic process with three important properties:

- Markov property,
- Independent increments, and
- Changes are normally distributed.

The Markov property means that the current value of the process is all one needs to make a best forecast of its future value; the process is otherwise independent of its history. More formally, the probability distribution of a variable (x_{t+1}) following a Markov process depends only on the current value of the variable (x_t) , and not additionally on what happened before time t . “Independent increments” means that the probability distribution for the change in the process over any time interval is independent of any other (nonoverlapping) time interval. The third property states that changes in the process over any finite time interval are normally distributed, with a variance that increases linearly with the size of the time interval.

A Wiener process for variable z is defined by the relationship between a change in the variable dz and the corresponding time interval dt

$$dz = \varepsilon_t \sqrt{dt} \tag{2.7}$$

where ε_t is a normally distributed random variable with a mean of zero and a standard deviation of 1. The random variable ε_t is sequentially uncorrelated, meaning that the expected value of the product of two random choices of ε is equal to zero:

$$E[\varepsilon_t \varepsilon_s] = 0 \text{ for } t \neq s. \quad (2.8)$$

Thus the values of dz for any two different intervals of time are independent, thus mathematically defining a Wiener process.

The simplest generalization of a Wiener process is Brownian motion with drift:

$$dx = \alpha dt + \sigma dz, \quad (2.9)$$

where dx is the change in a variable x and dz is the increment of a Wiener process as defined earlier. The drift parameter is α and the variance parameter is σ . Over any time interval dt , the change in x , written dx , is normally distributed, with expected value

$$E[dx] = \alpha dt \quad (2.10)$$

and variance

$$v [dx] = \sigma^2 dt. \quad (2.11)$$

The variance of the change in a Wiener process (dx) grows linearly with the time horizon. Because standard deviation is the square root of variance, the standard deviation grows as the square root of the time horizon.

Geometric Brownian motion with drift is a stochastic process in which changes in x are lognormally distributed, and is thus useful for modeling variables that cannot fall below zero, such as stock prices. If

$$F(x) = \log x \quad (2.12)$$

then the following simple equation for Brownian motion with drift applies:

$$dF = (\alpha - \frac{1}{2} \sigma^2)dt + \sigma dz \quad (2.13)$$

Over a finite time interval dt , the change in the logarithm of x is normally distributed with mean $(\alpha - \frac{1}{2} \sigma^2)dt$ and variance $(\sigma^2 dt)$. The expected value of x itself, if its current value is x_0 , is

$$E[x(t)] = x_0 e^{\alpha t} \quad (2.14)$$

which looks exactly like the formula for the future value of a sum of money x_0 at time t and interest rate α . Thus, this result for the expected value of a variable x following a

geometric Brownian motion process can be used to calculate the expected present discounted value of $x(t)$ over some period of time. The foundation for stochastic processes described in this section will be used in both of the models developed in this research.

2.6.3. Real options developments

The field of “real options” has emerged to value options on real assets (i.e., tangible, physical projects) as opposed to financial assets (Trigeorgis, 1996; Amram and Kulatilaka, 1999; Copeland and Antikarov, 2001). The two basic concepts of real options can be summarized as determining a) how exposure to uncertainty can be reduced and b) how payoffs can be increased if there is a good outcome (Amram and Kulatilaka, 1999). There are two types of real options: real options “on” projects and real options “in” projects (Wang and de Neufville, 2004). Examples of real options “on” projects include options to produce aircraft (Miller and Clarke, 2004), to explore and develop a copper mine (Moel and Tufano, 1998), and to redevelop land (Childs et al., 1996). Real options “in” projects are distinguished by the need for engineering system design to provide technological flexibility to take action in the future. Examples of real options “in” projects include a dual fuel boiler that burns both gas and oil (Kulatilaka, 1993), structural reinforcement to make future additions to a parking garage (de Neufville et al., 2005), and a reconfigurable satellite constellation that enables progressive additions to capacity (de Weck et al., 2003).

Real options valuation methodologies can be generally classified by the assumptions made and mechanics of applying the approach (Borison, 2003). The type(s) of uncertainty considered and the availability of data fundamentally determine the necessary assumptions and mechanics of a model. Financial-type real options models are those that are used to value options traded in financial markets (e.g., options on buying/selling stocks); they include mathematically derived formulas (e.g., the Black-Scholes formula), binomial lattice models, and other numerical solutions to mathematical descriptions of the option. Financial options are characterized by random fluctuations in the value of the underlying asset that can be described using the random walk theory of geometric

Brownian motion. The volatility of the underlying asset is one of the fundamental inputs to financial-type models. Volatility is derived either from historical data or from a separate model of the value of the underlying asset. Financial options models are primarily concerned with determining the value, or price, of the option itself; they do not inherently provide information on how the entire value of a project is shifted to benefit from upside potential while being protected from downside losses.

Simulation type models use random draws from probability distributions to model the outcome of an option-based scenario. Simulation allows for any choice of distribution on the underlying asset and inclusion of non-market based uncertain variables (Longstaff and Schwartz, 2001; Borison, 2003). Therefore, simulation models can have a more complete description of project value as compared to financial-type models. However, consideration of non-market (i.e., technical) uncertainties represents a great departure from classical options theory, which provides the rationale for risk-free discounting. Research is needed to understand the generality of models of flexibility in technical systems (Neely and de Neufville, 2001). There is great potential in using simulation models to provide advice to engineering and architectural decision making because of their ability to capture relevant uncertain variables, both technical and market, and to provide results that can be communicated intuitively to decision-makers (as opposed to results from black-box, complicated formulas).

RO methodologies are advantageous over DA methodologies for valuing flexible, dynamic strategies in project decision-making under several conditions. First, when there are a large number of time periods, a decision tree quickly becomes an unruly bush because the number of branches increases at an exponential rate. The RO methodologies, including analytical solutions, binomial lattices, and simulation, are more manageable under large numbers of time periods given the computing power available on typical personal computers. Second, when the major source of uncertainty is market-based, options methodologies are the more theoretically correct approach as compared to decision trees because of their continuous treatment of market risk. DA analysis assumes a constant discount rate throughout the entire analysis, whereas options pricing equations

derived using financial assumptions justify that the risk-free rate of return applies, thus negating the need to choose a risk-adjusted discount rate. However, when the major uncertainties affecting an option on a real asset are technical or private in nature, other methodologies are needed, such as simulation or combined options-decision tree approaches. Financial methodologies, as defined for this research, make the basic assumption that the uncertainty in the value of the underlying asset is characterized by a normal or lognormal probability distribution and that changes in value are described by geometric Brownian motion (GBM). Therefore, use of financial-based methodologies requires justification of market-based behavior.

The most acceptable way to satisfy the complete market requirement is to establish that a competitive, liquid market exists for the underlying asset (Trigeorgis, 1996). Market completeness means that there exist sufficient possibilities for substitute investments and that these range of investment possibilities can be readily acquired or divested. The first step to determine if a financial-type options model can be used for a real options valuation is to identify the underlying asset and the nature of its uncertainty. Next, it must be established that

- Changes in the value of the underlying asset are (at least partially) random, and
- A replicating portfolio can be constructed.

Establishing these factors is most apparent when the value of a project is almost *completely* determined by a commodity or otherwise market priced product of the project. The price of rent for a particular space-type in a particular location is one example and is discussed in detail in Chapter 4. Another example is use of the prevailing market price of copper to value an option to develop a copper mine. However, the value of the project is also determined by non-market factors (e.g., capacity of the mine and labor costs), thus stretching the assumptions needed for applying a replicating portfolio methodology. Thus, any analysis that uses financial-options methods for valuing real options needs to point out clearly that the analogy between real options and options on stocks is not exact. According to Trigeorgis (1996), several of the distinguishing characteristics of real options as compared to stock options are non-exclusiveness of ownership, competitive interaction, non-tradability, and compoundness (i.e., multiple options dependent on each

other). Thus, the replicating portfolio justification is the assumption that is generally farthest from the theoretically correct application of financial options models to real options.

2.7. Review of project evaluation research for buildings

Models for calculating building costs, visual impact assessment, thermal analysis, and sustainability benchmarking for buildings are now widely available, and often the user has many to choose from (Timmermans, ed., 1993; MIT Design Advisor; NIST Building Life-Cycle Cost Program). However, design and decision support systems are not as widely employed in the building industry as in many other industries, partly because of its non-homogeneity (Timmermans, ed., 1993). According to Raftery (1991), the history of models for building cost and price can be classified into three generations: elemental data bases of costs (1950s-1960s), regression analyses (mid 1970s-today), and probabilistic consideration of uncertainty in costs (1980s-today). Recent developments in life-cycle-costing, uncertainty analysis in building design evaluation, and application of real options to real estate are discussed herein.

Kats et al. (2003), motivated by the real estate industry's widespread perception that green buildings are significantly more expensive than conventional design and construction practices, conducted a thorough study of the life cycle costs and financial benefits of green buildings in a research effort for California's Sustainable Building Task Force. This is the most comprehensive work on the topic of the financial implications of green building design, including risk, and many of its findings are relevant for this research. The overarching purpose of the report was to determine if it makes financial and economic sense to build a green building based on cost data gathered on 33 individual LEED registered projects (25 office buildings and 8 school buildings). The data represent projects whose designers had a range of green building experience, and thus that data represent a range of cost premiums and savings. The results conclude that the average reported cost premium is somewhat less than 2 percent. Furthermore, that two percent increase in upfront investment typically yields life cycle savings of over ten times the initial investment.

Kats et al. (2003) state that the financial benefits of green buildings range from being fairly predictable, such as the expected cost savings for energy, waste, and water, to relatively uncertain, such as productivity and health benefits. The statement that “expected costs savings for energy, waste, and water” are fairly predictable is debated in this research. Expected values of savings are only realized upon building conception if systems operate as designed, if climate acts like the assumed typical mean year data used in an energy analysis, and if there are no technical problems. Furthermore, because of the uncertainty represented by these “if” statements, designers often over compensate for systems that they have little experience with, thus reducing the true cost savings potential. Additionally, the uncertainty may also result in beneficial outcomes that are not capture by expected value analysis. These observations are particularly applicable to passive building design, such as natural ventilation, which require detailed consideration of a range of operating conditions. The industry’s comfort level with expected value based design and estimates of benefits serves as a barrier to adoption of advanced, integrated architectural and building system designs.

It is difficult to compile representative data on the costs of green building attributes for a variety of reasons (Kats et al., 2003). First, many developers keep cost information proprietary. Second, individual green items are not always priced out in comparison to non-green alternatives. Third, some green buildings being built today are showcase projects whose costly finish upgrades are not distinguished from the green building features. Fourth, the design and construction process for a firm’s first green building is often characterized by significant learning curve costs and design schedule problems such as late and costly change orders. Fifth, the relative newness of green technologies and systems can make designers, architects and clients conservative when using them. They may oversize green building systems and not fully integrate them into the building, thereby reducing cost savings and other benefits. This last observation indicates the need for decision-making support on the financial implications, risks, and rewards of using innovative, green building technologies.

There are several examples in the literature of methodologies to incorporate uncertainty into decision models for building technologies. Zmeureanu and Pasqualetto (2000) include uncertainty in their models for choosing among energy conservation measures in office buildings. Pace and Gilda (1998) account for the potential variability in cost parameters for exterior wall systems, resulting in probabilistic information on the total costs of the various wall systems. Flexibility, or dynamic planning, is not included in either of these studies. De Wit and Augenbroe (2002) use uncertainty analysis to find expected value of thermal comfort. They then use utility analysis, based on Bayesian decision theory, to choose between natural ventilation and mechanical cooling for a building in the Netherlands based on optimizing two parameters: investment cost and thermal comfort. The paper introduces uncertainty and utility analysis into the decision making process of design, but it does not go so far as to address flexibility as a design strategy. It also does not address life cycle costs, consideration of which could greatly influence the choice between natural ventilation and mechanical cooling. In summary, although these studies set a precedent for consideration of uncertainty in design decisions for buildings, they do not include the flexibility to make on-going decisions in the future as uncertainties are resolved.

Several authors present methodologies to value flexibility building design strategies under uncertainty where future decision points are included in the analysis. Prins et al. (1999) suggest a design and decision process for optimizing building flexibility and minimizing life-cycle costs. The process includes writing a flexibility scenario as part of the initial design brief, in which assumptions are clearly stated about all relevant social, political, and cultural events, which may influence the use of the building. Building change and flexibility are incorporated into the model of building costs, but the model does not include simulation capabilities (Prins et al., 1999). Friedman (1999) illustrates the use of decision theory using expected (monetary) value and weighted utility to assess choices of flexible internal partitions in multi-unit housing. The author evaluated five design alternatives using a decision tree. The value of each alternative is defined as the assumed life cycle savings potential in dollars based on estimates from contractors and the author. The probabilities that the savings potentials are realized are based on surveys

of occupied projects and the architect's subjective judgment. Utility analysis is used to select among the various alternatives, where 'savings potential' is one of five objectives (Friedman, 1999). These examples demonstrate that, as in most decision models concerned with modeling future outcomes, subjective opinions are often necessary, especially where similar historical data does not exist and if historical data is not expected to be a good indicator of future events.

To date, the real options literature has considered applications of options theory to several relevant questions for real estate development characterized by options "on" underlying assets. Geltner (1989) applied a financial option-pricing model to explain the phenomenon of vacant urban land. Geltner et al. (1996) used a perpetual option model to provide insights on the effect of land-use choice. Patel and Paxson (2001) use a perpetual American call option model treated as an exchange option to value a) properties under construction and b) properties held for development at the Canary Wharf development project (prime office space) in London. Kalligeros (2003) addressed the design-lifetime of a group of buildings, recognizing uncertainty in future demand in the region. Each of these authors supported the argument that the underlying assets of land and property value follow a geometric Brownian motion process.

Fawcett (2002) proposed the idea of using options methodologies for life cycle costing of buildings. According to Fawcett (2002), two of the difficulties encountered when attempting to operationalize financial-type options models in the construction industry are (1) data is not usually available and (2) professionals in the construction industry are not familiar with the mathematics behind the techniques. There is a need to develop a better understanding of the dynamics behind construction and building relevant underlying assets if the goal of use by industry is to be achieved. Furthermore, much of the published literature on options focuses on market risks. When the exercise of an option requires technical understanding of the system and when technical, non-market constraints enter the decision, the valuation of an option departs from much of the published literature.

2.8. Chapter conclusion

The literature review suggests three implications for this research. First, there is a need to address the risk concerns of real estate investors to help improve the attractiveness of investment in innovative, sustainable building technologies. Second, although examples of flexible building design are providing evidence of improved value, there is a need to provide decision-makers with evaluation tools for making investments in flexible designs. Third, real options provides a way forward for strategically designing and valuing flexible designs. Building projects, when thought of as a portfolio of systems that may change over time, require a similar approach to flexibility as in investment decision-analysis. The real options literature has only begun to explore the topic of investment in elements of flexibility in engineering systems. This research aims to fill that gap for architecture and engineering systems by quantitatively and formally applying flexibility concepts to design and decision-making for buildings and other technical systems. Flexible, or options-based, design holds the potential to reduce the risk of sustainable building designs while also positioning them for realizations of greater value.

3. A Real Options Based Approach for Architectural and Engineering Design

A real options approach to architectural and engineering design is presented in this section. The methodology fits within the overall context of a generalized design process, as shown in Figure 7. When the object of design is subject to uncertainty in its future operation or operating environment, this real options approach to flexible design will help architects and/or engineers achieve an improved design. The approach provides a framework for considering uncertainty during the design phase, identifying potentially valuable elements of design flexibility to address the uncertainty during the object’s operational life, and it provides guidance for assessing the value of flexibility and use of the assessment for decision-making.

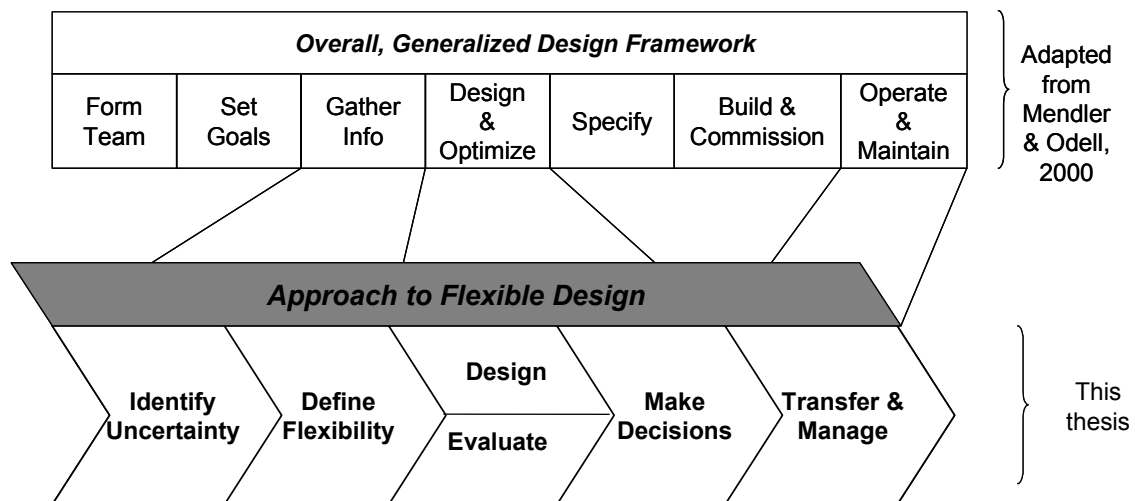


Figure 7. A real options approach to the design and valuation of flexibility in engineering and architecture systems set within the context of holistic, sustainable design. (Source of overall design framework: Mendler and Odell, 2000).

The real options approach will readily find a home within sustainable design for buildings as it meets two distinct needs: enhanced building longevity via flexibility in space-use (i.e., enabling adaptive reuse), and, second, employment of nonstandard, innovative technologies via flexible design that reduces risk. The process is conceptualized in five steps, as shown in Figures 7 and 8:

- Identify uncertainties,

- Define flexibility,
- Design and Evaluate (with a real options approach to modeling),
- Make Decisions, and
- Transfer and manage.

As shown in Figure 7, the first four steps of the flexible design approach span the entire design period, while the fifth step requires activity throughout the operational phase, or lifetime, of the project.

It is important to set the flexible design approach within a holistic design context, as it facilitates necessary prerequisite conditions. Mendler and Odell (2000) outline a seven-step holistic, sustainable design approach, as shown in Figure 7: team formation; education and goal setting; gathering information; design optimization, documents and specification; bidding, construction, and commissioning; and operations and maintenance. One condition for real-options based design, and for sustainable design alike, is that the design-phase team includes all design disciplines (e.g., both engineers and architects), owners or developers (i.e., the investor decision-makers) and the operators of the project during its lifetime. This diverse team is necessary to identify uncertainty and physical elements of flexible design that will enable the options-based operational strategy. A second facilitating role of holistic design is that it provides for goal-setting. Within this context, the goal of flexibility may be established. The corollary to this goal is that management (e.g., building operators and owners) will operate the asset in light of its flexible components. Without agreement that flexibility will be actively managed during the project's lifetime, assessment of the value of flexibility is meaningless. Thus, the real options approach reinforces the importance of team formation and goal setting.

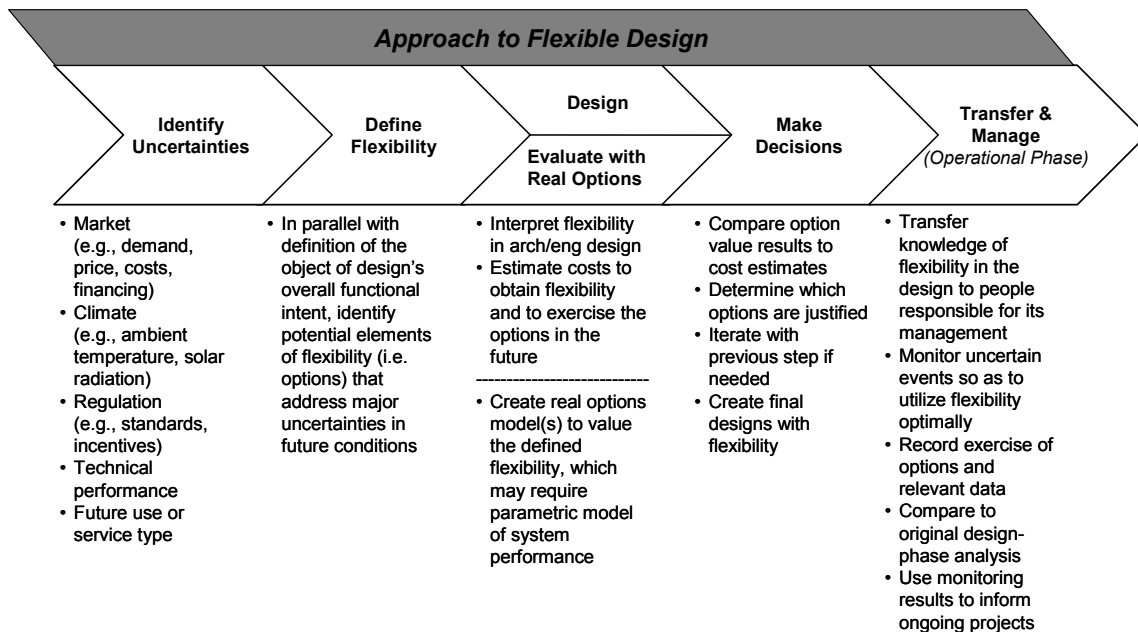


Figure 8. Actions taken at each step of the real options approach to flexible design.

This chapter focuses on the specifics of the real options approach to design so as to provide guidance to design teams that have already defined consideration of flexibility as a goal. The first two steps, ‘identify uncertainty’ and ‘define flexibility,’ occur within the information gathering phase of the holistic design process. The next two ROs steps, ‘design and evaluate’ and ‘make decisions,’ occur with the design optimization phase. The reinforcing relationships between the holistic design process and the real options design approach are discussed. The real options approach includes evaluation of the monetary value of flexibility, based on recognition of the value of flexibility in the life cycle phase, and thus may be used within life cycle costing (LCC) decision-making methods. Finally, the value of flexibility will only be realized if knowledge of flexibility is maintained. The real options approach to design suggests an opportunity for enhanced, long-term relationships between designers and those who manage the project during its lifetime. The chapter begins by arguing for the role of physical design as a facilitator of risk management and henceforth describes the individual steps of the real options approach to design, as detailed in Figure 8.

3.1. The case for design as a facilitator of uncertainty management

A flexible, options-based design, defined as one that provides operational managers of a technical system means to avoid losses and/or take advantage of opportunities as they arise, is a form of risk management. In the discipline of finance, financial options are used to accomplish the same objectives of risk avoidance and opportunity exploitation. Management of uncertainty at the project level has typically been left to the discipline of finance in the form of balancing portfolios of risky projects (i.e., ones subject to uncertainty). Indeed, much of the work to date in the field of real options has focused on managing uncertainty at the project level through options to expand, delay, or shut-down a project at a given stage. In contrast, flexibility at the technical level, via options within systems, presents a means of avoiding risk and exploiting opportunities at the operational level of the project.

Engineers and architects are well equipped to facilitate uncertainty management within a project through technical design. To begin with, based on their collective experience and expertise, they are generally knowledgeable of the uncertainties that affect the systems they are responsible for designing. They know the design constraints, generally accepted practice for making designs robust within uncertain operating environments, and are trustees of customer specifications. Designers know how to simplify complex, uncertain design goals, and they have generally accepted rules for applying safety factors to protect against the possibility of failure. Furthermore, engineers and architects currently address maintenance and quality issues of the projects they design. The real options approach, or design for flexibility, expands these concepts to consider active management of a system that is able to transform. Thus, designers have a knowledge base for uncertainty identification; the real options approach suggests a new way for addressing uncertainty by design, one that will lead to improved risk/reward profiles of the project.

The design process for multi-objective, multi-parameter systems, such as buildings, necessarily entails feedback loops and integration among systems. Addition of uncertainty to the shared parameters among parts of a system increases the complexity of

achieving an optimal design. Thus, when multiple uncertainties exist, it becomes increasingly complex to design a system with options, or elements of flexibility, that can be managed optimally. Flexible design innately requires an integrated design process with communication among the design disciplines and decision makers (e.g., the client). This represents a departure from typical design processes, which too often occur sequentially. For example, in building design, engineers are traditionally handed the blueprints to which they add mechanical and electrical systems with little input on the overarching structure. This sequential process leads to oversized mechanical systems. However, the concept of flexible design is not out of reach of the typical design process, and demonstration of its benefits will help bridge the gap between sequential and integrated processes. Equipped with the capabilities to achieve flexible design, the remaining link is to communicate the benefits that options-based design offers to decision makers. Real options analysis provides this link.

3.2. Identify uncertainties and subsequent risks

The first step, *identify uncertainties*, guides the remainder of the process. By understanding the uncertainties that will affect the performance of the system, flexibility can be defined so as to a) reduce risk and b) take advantage of possible upside opportunities. This stands in contrast to typical practice in which uncertainty is either ignored (i.e., assumed to be zero) or addressed to the fullest negative extent through design for the worst-case scenario.

Uncertainty can be understood by imagining that an uncertain variable may result along a continuum, ranging from a good, or *upside*, outcome to a bad, or *downside*, outcome, and somewhere in between lies the *expected* outcome. The performance of a system depends on the realization of the uncertain variable in practice. At the design and investment stage, projects are generally evaluated only under expected conditions. Additionally, systems are often designed to ensure acceptable performance even if the downside outcome of the uncertain variable occurs, despite the performance of this worst-case scenario design under expected conditions and despite a low-likelihood of the downside outcome. Oversized HVAC systems that cannot be operated efficiently at part load are

an example. On the other hand, sometimes, uncertainty is simply ignored. This occurs when uncertainty is considered to have intangible outcomes or not to be relevant to the initial investors. Design of a space for a single-purpose use, despite the prevalence of churn and renovation, is an example of ignoring uncertainty at the design phase. Flexible, options-based design not only requires identification of uncertainty, but also the willingness to address the full range of performance possibilities under uncertainty.

Risk and opportunity, by definition, arise from uncertainty. In the discipline of finance, uncertainty and risk are classified as either unique or market type. A unique risk is one that can potentially be eliminated by diversification (Brealey and Myers, 2000). In contrast, a market risk is one that cannot be avoided, regardless of how much a manager diversifies (e.g., portfolio of different projects or stocks). For design of technical systems in the face of uncertainty, it is more useful to think in terms of both the upside opportunities and downside events, or risks, that may occur. Furthermore, flexible design can address *any* type of uncertainty; therefore, the financial concepts of distinguishing between diversifiable and undiversifiable risk do not apply to designers.

The classes of uncertainty applicable to designers are shown in Table 3 along with the financial categorization. The five categories of uncertainty applicable to design are market, climate, regulatory, technological, and future use. Each uncertainty ultimately has a financial impact, but this categorization differentiates the sources of uncertainty. Table 3 lists examples of uncertainties in each class that are relevant for innovative (design of) technologies and systems, particularly for environmentally beneficial technologies such as sustainable buildings and renewable energy systems.

Table 3. Classes of uncertainty for innovative technologies

Uncertainty class		Examples of uncertainties	Data source or means of quantification
<i>In Finance</i>	<i>In Design</i>		
Market risk (i.e., undiversifiable)	Market uncertainty	<ul style="list-style-type: none"> – Demand for product/service provided by system – Price of product/service – Price of inputs (e.g., energy prices) 	<ul style="list-style-type: none"> – Historical data (if available) – Expert opinion
	Climate uncertainty (for systems whose performance depends on climate)	<ul style="list-style-type: none"> – Future ambient climate (temperature and solar radiation) – Global climate change and warming trends 	<ul style="list-style-type: none"> – Stochastic climate models based on historical data and global climate change inputs
	Regulatory uncertainty	<ul style="list-style-type: none"> – Introduction of new standards for existing facilities – Future availability of tax credits or other incentives 	<ul style="list-style-type: none"> – Expert information and opinion
Unique or technical risk (i.e., diversifiable)	Technological uncertainty	<ul style="list-style-type: none"> – Success/failure of new technology – Introduction of new, superior technology 	<ul style="list-style-type: none"> – Expert opinion – Stochastic models of system performance
	Uncertainty in future use of real estate and/or land	<ul style="list-style-type: none"> – Changes in service type or intensity given initial service intent – Rate of change 	<ul style="list-style-type: none"> – Expert opinion – Historical data

Market uncertainties directly impact the financial attractiveness of a project by affecting the costs and revenues. Examples of market uncertainties include the market price of the product being produced, operating costs as influenced by energy prices or other commodities, costs of equipment that may be installed at a future date, and financing terms. For buildings, the type of space (i.e., office, laboratory, retail, etc.) is the most common value determinant for a given geographical location (Bottom et al., 1999). Market risks for a product or service that use innovative technologies include greater uncertainty in the future (sales or rental) value due to uncertainty in market acceptance of

the innovative features. The future value of a building labeled as “green,” for example, is uncertain partially due to market, or consumer, acceptance of its features. However, as the recognition and awareness for green buildings increases, so might the value of buildings with green attributes. Each of these examples represents a risk or opportunity that stems from uncertainty in the market price of a product.

The next four categories of uncertainty – climate, regulatory, technological, and future use - are specific to the project, technology, or location of interest. These categories share the commonality that, if uncertainties evolve unfavorably, expenditures will be needed to correct the problem and bring the system to a productive state. Alternatively, the sub-standard system will not be able to obtain its full profit potential, all other things equal. Yet another alternative is to design a flexible system that, because of insurance-like options, can evolve so as to protect against losses if a downside outcome of uncertainty is realized. Likewise, flexible design can be used to position the system to benefit from positive realizations of uncertain climate, regulatory, technological, and future use events.

Climate uncertainties are especially applicable to the performance of environmentally beneficial innovative technologies, such as passive building designs and renewable energy systems. Uncertainty in climate is of utmost relevance to passive building design, such as natural ventilation, where designing with “design day” climate data does not suffice to understand daily operation of a building. The constantly varying ambient climate partially determines a building’s internal heating and cooling loads, and it directly determines the exterior air’s cooling capacity. Likewise, variations in solar radiation and wind speed determine how much energy is produced with solar photovoltaics and wind turbines. Furthermore, in addition to daily and seasonal fluctuations in climate, long-term climate change from greenhouse gases are also relevant for buildings and other engineering systems with long lifetimes, on the order of twenty or more years.

Future regulation is another uncertainty applicable to today’s engineering design decisions. Regulation may occur in the form of new physical (component) requirements,

performance requirements, or economic changes that impact costs. Government intervention may also provide opportunities for installation of an innovative technology in the future that may not have existed at the time of initial design. Credits for installation and use of renewable energy systems or for buildings that perform to a certain extent better than standard energy codes are two examples. Thus, it may be valuable for today's design to include the flexibility to take advantage of regulatory opportunities or protect from penalties that may be imposed.

Technological uncertainty refers to the functionality of a component, which is partly determined by the system in which it is contained. Demonstration projects are one area of government-supported work in reducing the risk of using innovative technologies (Loftness, 2004). At the same time, positive realization of technological uncertainty, meaning the technology functions at least as well as called for by project objectives, provide the owner of the technology with an option to expand its market. Another technological risk is that a superior technology will be introduced that competes with the system as originally designed. This risk may also affect the future worth of any options designed into a system, as they may become outdated.

Uncertainty in future use or demand for a system is particularly suited for options-based design and assessment. For example, a change in business direction may make laboratory space no longer useful to a company, and instead, office space or conference space may be needed. Building functionality, as determined by its design and set of renovation possibilities, is highly affected by such exogenous uncertainty. Changes in use or demand happen somewhere along the continuum bounded by a high frequency with a low intensity of change to a low frequency but with a high intensity of change. (High frequency with high intensity of change is also possible but uncommon). An example of the former is the desire to reconfigure office space to support formation of short-term working groups. An example of the latter is refurbishment of a building from laboratory to office space. Observable characteristics of change in building-use include changes in occupant density, types of office equipment, and flow of construction materials. To address the risk of building obsolescence and to position the building to

evolve optimally in the face of change, flexibility scenarios are needed in the initial design briefings.

The team that undertakes uncertainty identification should consist of all design disciplines (e.g., both engineers and architects), owners and/or developers, and the operators of the project during its lifetime. Table 3 can be used to guide discussion on the major uncertainties pertinent to the design at hand as well as to gather quantifiable information about the uncertainties. Another approach that may be used to identify uncertainties is scenario analysis, where the team describes the system (e.g., building), as it would exist in different possible states of the world (Cooke, 1991). Scenario analysis does not yield predictions but rather a depiction of the object in a range of uncertain outcomes. With the list of major uncertainties that might impact the success of the project, the team can then reduce the list to those uncertainties that are agreed to be of most importance and/or those that can be addressed with flexible design. This refined list of uncertainties will depend on each particular design situation – the building’s location, the activities that take place in the building, and the technologies under consideration.

The uncertainties are to be quantified to the extent possible using historical data, modeling exercises, and expert opinion. Three questions to address for any presumed representation of uncertainty are as follows (Cooke, 1991, p. 61):

- Does it account for the interactions between events or propositions?
- Does it explain how uncertainty is affected by observation? (e.g., might uncertainty be reduced by gathering more data)
- If the uncertainty quantification is derived from opinion, does it enable ranking of the validity of one expert’s opinion over another?

While the third question is pertinent to research in the field of uncertainty analysis with expert opinion, the first two questions are useful for design projects in that they suggest probing the relationships between sources of uncertainty and the possibility that uncertainty may be reduced by a data-gathering effort. The quantified uncertainties will be used in the third step, where the value of flexibility is assessed with a real options model. However, first the flexibility must be defined.

3.3. Define flexibility

The identified uncertainties provide the clues for *defining flexibility*, the next step in the real options design approach. For example, uncertainty in the direction of a business unit indicates potential value in being able to change the use of the space that it occupies. Alternatively, uncertainty in the local real estate market for the price of an office space lease may make it valuable to be able to provide for as much of your own office space needs as possible rather than have to pay a market rate of rent. As another example, the probable, yet uncertain, decreases in the future costs of photovoltaic panels may warrant a wait-and-see strategy of having the option to install the panels in the future. Uncertainty in prices of conventional, utility provided electricity; the building's electric loads; and future tax credits or other rewards for using renewable energy sources add to the potential value in being able to install photovoltaic panels in the future. The key point is for the team to address the most relevant uncertainties with flexible design.

To introduce flexible strategies into engineering and architectural design, it is useful to define two broad categories of flexibility: “macro,” which describes changes that happen once or otherwise infrequently, and “operational,” which may be described as adjustments in response to inputs that fluctuate on a shorter time-scale, such as hours or days. The structure of any particular case may involve a combination of macro and operational components of flexibility. For example, if the macro flexibility of an option to install mechanical cooling is exercised, the operational flexibility of choosing between outdoor air and mechanically conditioned air is enabled. Table 4 provides a summary of the macro and operational categories of flexibility and a few examples.

Table 4. Categorization of flexibility into macro and operational types

Category of Flexibility	Macro	Operational
Time scale	Infrequently – Once or a few times over the entire project lifetime	Frequently – Hours, days, or months – Multiple times over project lifetime
Examples	– Change the type or use of a space – Install mechanical cooling in an otherwise naturally ventilated building	– Change the activity within a space – Choose between using outdoor air or mechanical cooling in a hybrid cooling system

Another way to categorize changes in buildings is given by Slaughter (2001): changes in a) the function of the space, b) in the load carried by systems of the building, and c) in the flux of people and forces from the environment. For this research, such a categorization is useful for identifying uncertainties that affect a building and its systems. For example, changes in climate (c) from hour-to-hour partially determine the load (b) carried by HVAC systems and thus affect the level of *operational* flexibility needed to control the building’s interior environment. On the other hand, long-term climate change (c) and/or changes in building function (a) will also affect the expected HVAC system load (b), which may justify *macro* flexibility of the option to install mechanical cooling in an otherwise naturally ventilated building. As described, changes in a building’s services can occur at both the macro and operational levels.

Likewise, changes in the use of a space occur at both the macro and operational levels. One of the case studies conducted herein is of a corporation whose campus has seen many of its buildings change at the macro-level, including conversions of laboratories to offices, pilot plants to laboratories, and closed offices to open-plan type offices. Another macro-level example is the telecom server building with option to convert to an office building as described in Chapter 2. The flexible design of the telecom building was motivated by the uncertainty in future demand for server-type buildings, which the designers knew would become better understood as the design process evolved

(Batchelor, 2003). In the operational category, examples include changing the type and scale of experiments in a laboratory and reconfiguring office space (without major renovation). The example of Millennium Laboratories, described in Chapter 2, melded the distinct functional requirements of chemistry and biology labs into a single design that allows for both types of experimental work, thereby facilitating productive changes as business-needs fluctuate. In summary, classification of flexibility into macro and operational categories is useful for structuring a real options model. The candidate elements of flexibility and the uncertainties they address guide development of a real options model.

3.4. Design and Evaluate with a ROs model

The *design* and the *real options evaluation* steps occur in parallel. This thesis focuses on the development and use of real options models to aid decision-making, and only qualitative attention is given to flexible design typologies. However, in practice, parallel development of the flexible design and real options models is necessary, as the cost estimates for the physical design are to be compared to the results of the real options model in the ensuing step. In this section, a few guiding thoughts on flexible design are provided. More in-depth guidance is given to choice of a type of real options model for conducting the economic analysis of the value of flexibility.

3.4.1. Design

Design for flexibility will probably be most effective when it is initiated in the early, preliminary design phases of the overall design process (e.g., conceptual or schematic design). In the preliminary design phase, the team of architects and engineers begins to provide physical meaning to the candidate elements of flexibility. Inclusion of flexibility early on in the design process enables integration of flexibility within other design goals and requirements. In this context, *integration* translates to *separation* of flexible components from inflexible components so as to enable change where it is valuable while preserving static elements that provide structure to the design. The level of flexibility of a design can be defined by the tradeoff between intensity of initial investment and (potential) future exercise costs. Thus, several schematic designs representing various

levels of flexibility should be outlined. From the set of alternative designs, initial estimates are made of a) the costs needed to gain the flexibility and b) the costs that would be entailed in the future to exercise the option.

Achieving integrated, flexible design calls for cooperation among all decision-making parties, as the capacity for realizing the benefits of flexible design must be initialized from the start. This includes the aforementioned need for architects and engineers to work in a parallel process so as to properly integrate different elements of the (flexible) design. It is reasonable to postulate, based on experience in the typical design process, that the ability to include flexibility in a design is reduced exponentially in each subsequent phase of a design process as changes will be more difficult and thus costly to make. Communication among all decision-making parties, including investors and clients, and an integrated design process are essential to a real options approach to design.

3.4.2. Evaluate with real options

In parallel with the design activities, a real options evaluation process is undertaken to demonstrate the value of the flexible system under uncertainty. Modeling activities will yield the monetary value of flexibility and other appropriate performance indicators of the flexible design. Traditional, or financial-type, real options models are concerned only, or primarily, with a price of flexibility, to which the cost estimates for the flexible design are compared. In addition to the price of flexibility, other modeling goals to be considered when creating new types real options models applicable to design scenarios include providing information on the likelihood of exercising the option, demonstrating the range of performance levels, and providing measures of non-monetary cost-benefit indicators of the system. A guide to creating a real options evaluation model applicable to flexible design, based on the type of uncertainty or uncertainties addressed by the design, is given in Figure 9.

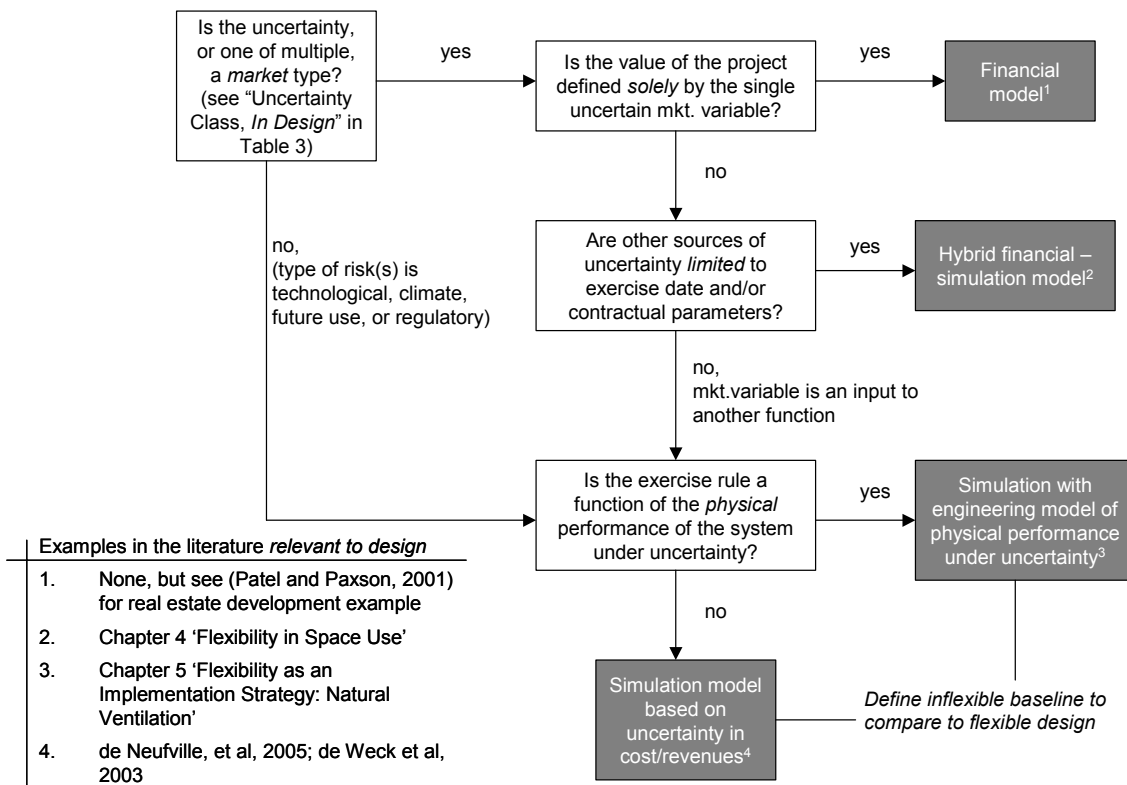


Figure 9. Expert decision tree for guiding choice of real options modeling approach.

Choosing a real options modeling approach begins with the identified uncertainties that the flexible design addresses. Table 3, presented in the ‘identify uncertainties’ step, classified uncertainty for physical systems into categories of market, climate, regulatory, technological, and future use. As shown in Figure 9, if one of the sources of uncertainty is a market variable and if the value of the flexible design is defined solely by the (single) uncertain market variable, financial methodologies may be used to provide guidance on the value of the flexible design. Examples of financial methodologies include the Black-Scholes formula for call options (Black and Scholes, 1973; Brealey and Myers, 2000), the Samuelson-McKean formula for perpetual call options (Geltner and Miller, 2001), and the binomial lattice model (Cox et al., 1979; Copeland and Antikarov, 2001). With

regards to flexibility in design, there are no examples in the literature in which a pure financial options model is applied to guide design questions. This likely stems from the multiple sources of uncertainty applicable to design. However, several examples of financial option models applied to land and real estate development have been published, including Geltner (1989), Geltner et al. (1996), and Patel and Paxson (2001). If the major source of uncertainty is from the market, and if the other sources of uncertainty are limited to the timing of the exercise date and contractual parameters surrounding the market variable, a hybrid financial-simulation model is appropriate. In a hybrid financial-simulation model, a financial model is used as the basis for determining the value of an option, assuming complete market conditions exist, and Monte Carlo simulation is added on the other uncertain terms within the financial model. The study of flexibility in space-use presented in Chapter 4 is an example of a hybrid financial-simulation model.

If, as shown in Figure 9, the major source of uncertainty is a non-market variable (i.e., technological, climate, future use, or regulatory) or if the market variable is an input to another function that determines project value, then the next question is whether or not the exercise rule is based on the physical performance of the system under uncertainty. If the answer is no, meaning exercise is based on economic rather than physical terms, then a simulation model based on a cost-revenue model under uncertainty is appropriate. Examples of simulation models based on cost-revenue models for flexible designs include a structurally reinforced parking garage that allows addition of levels if demand increases (de Neufville et al., 2005) and staged deployment and reconfiguration of a satellite to respond to increase in demand (de Weck et al., 2003). However, if exercise of the design's flexibility, or real option, depends on how the system performs physically in the future, then a simulation model that includes an engineering model of the system's physical performance under uncertainty is needed. The study of the option to install mechanical cooling in a naturally ventilated building, to address the risk of overheating under climate uncertainty, presented in Chapter 5 is an example of a simulation model that includes a model of physical system performance. This real options valuation model

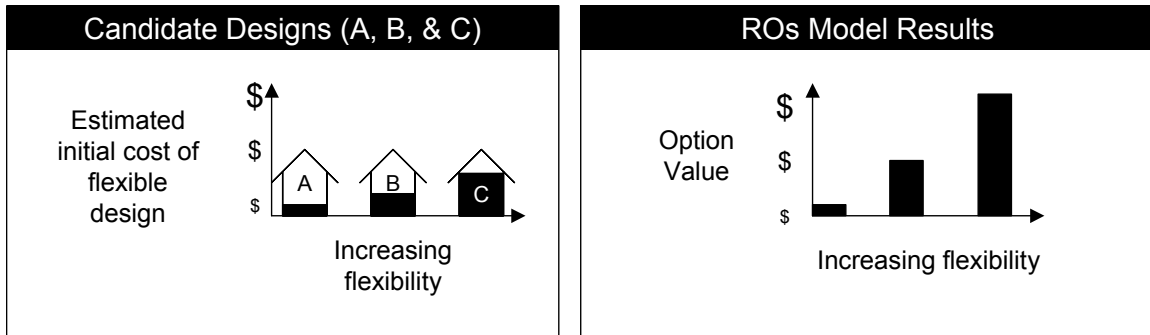
is the first in the literature to address uncertainty in a system's performance and use it to value a flexible design.

To set up a simulation model for a real options analysis, it is necessary to define a *flexible* and an *inflexible*, or baseline, case. The difference in project value of the flexible and inflexible cases is the option value, or value of flexibility (Moel and Tufano, 2000). Cases involving more than one option will require *compound option* models if the individual options depend on the outcomes of other options, either simultaneously or sequentially (Copeland and Antikarov, 2001).

The goal of a real options analysis for design is to evaluate a range of strategies with different levels of flexibility, so as to provide information on the tradeoffs between initial investment in flexibility and later costs associated with exercising the flexibility (if it occurs). The real options analysis also results in a set of rules for managing the flexibility during the operational phase of the project. Throughout the design and real options evaluation process, communication needs to occur between the two groups so that information about the physical design can inform development of a relevant valuation model.

3.5. Use of results in decision-making

Next, the design and real options teams reconvene to compare the *results* of the design and real options analysis step. The cost estimates of the conceptual designs are compared to the option valuation results, as shown in Figure 10. With a better understanding of the technical means of achieving the flexibility, the real options valuation results can meaningfully guide decisions to invest in how much and what type of flexibility. The basic decision rule applicable for real options evaluations is the following: invest in the flexibility if the initial cost to obtain the flexibility is no greater than the option value, as shown in Figure 10. For design, it is useful to model various levels of flexibility so as to allow for tradeoffs between *initial* costs to obtain flexibility and the *future* cost of exercising the flexibility.



- Compare initial cost of flexible design to the results for option value (for a given level of flexibility).
- Decision rule: invest in flexibility if initial cost \leq option value.

Figure 10. The real options valuations results are compared to the cost estimates for decision-making.

Communication of options valuation results to decision-makers is a central issue to advancing options-based designs. Part of the hypothesis in this research is that the financial language invoked by a real options design and valuation process will be familiar to financial decision-makers. However, decisions to undertake flexible designs may go through multiple levels of decision-makers and may reach ones who are not familiar with financial calculation methods. A transparent calculation method and graphical representation of results are strategies that assist effective communication of results.

Graphical depiction of the (cumulative) probability distribution of results shows the range of possible outcomes. The information contained in the tails of a distribution is often a key factor in decisions about the design of major projects (de Neufville et al., 2005). Comparison of the option-based design results to those from an inflexible (or less flexible) design shows how the flexible project is able to take advantage of upside opportunities *and* protect from downside losses. Furthermore, displaying the results as a cumulative probability distribution allows decision-makers to deduce the value of the option-based design for different levels of certainty (de Neufville et al., 2005). For

example, a decision-maker may be interested in the maximum possible loss (or maximum possible costs) for a design. The 10th percentile value of the results provides the 90 percent certainty level for value (or costs). In other words, the 10th percentile result is that for which it is 90% certain that the level of value will (at least) be realized or that the level of costs will not be exceeded, according to the model. Thus, a table providing the following statistics for different exercise costs is recommended:

- Mean option value
- Maximum option value (or a similar measure such as the 90% cumulative probability value)
- Minimum option value (or a similar measure such as the 10% cumulative probability value)

Extraction of these statistics readily allow decision makers to see the expected, upside and downside outcomes indicated by the ex ante analysis.

Exploration of the flexible project for sensitivity to design parameters and assumptions on uncertain variables is a natural part of options-based design. Three primary variables (or effects) to test for sensitivity include exercise or delayed costs, the level of uncertainty in stochastic variables, and the time-frames over which the option is evaluated, including sensitivity of parameters that affect exercise. For example, in a real options analysis conducted by de Neufville et al. (2005) for the design of a parking garage under demand uncertainty, although building smaller at the start (and thus delaying capital expenditures) provided insurance against potential losses, the smaller size was still sufficient to make the project revenues attractive for initial investment. When formulated within a design context, a real options analysis provides a platform for assessing alternative designs.

To determine if an investment in a flexible design should be made, the option valuation results are compared to the estimated (design and construction) costs to achieve the defined level of flexibility. For example, suppose that the results for an exercise cost of \$15 yield a mean option value of \$100. This result suggests that the estimated design and construction costs of the option-based design (i.e., one that can be ‘exercised’ in the

future for \$15) can be up to \$100. If the estimated first costs are less than or equal to the value suggested by the real options valuation, then it is rational to invest in the project. However, not *all* flexibility is valuable. It may be too costly to obtain the element of flexibility. Decision-makers would then have to reconsider the flexibility under question and/or reject the candidate investment as defined in the real options valuation. Iterative designs and refinement of the model may be useful at this step. In each of the two scenarios studied in this research – flexibility in space-use and the option to install mechanical cooling in a naturally ventilated building – detailed discussion is provided on using real options valuation results for decision making in relation to the real-world issues relevant for each case.

3.6. Transfer and manage

Transfer and manage is the final, and long-term, element of the real options design strategy. This step begins upon construction and commencement of operation of the flexible system. Options-based design and its evolution require active screening of the factors that may make exercise valuable, as value will only be realized if knowledge of flexibility is maintained and used according to the decision rules provided. In the context of buildings, it is important that the building managers, owners and/or occupants are knowledgeable of the building's flexible capabilities, or real options, and the optimal strategies, or decision rules, for exercising them.

Active management of flexibility suggests two distinct roles for the designer. First, the designer needs to play an educational role to ensure that the knowledge of flexibility is properly transferred to the owner and/or operator. Second, flexible design presents an opportunity for the designer to maintain an ongoing relationship with the system operators so that the flexible design is managed optimally. In addition, retaining the original design firm may enhance the efficiency of exercising the option, if the need arises, so that transformation is executed according to the original design intent. This represents an opportunity for designers to provide an ongoing service to clients. Retaining a designer throughout the operational phase represents a drastic departure from

the traditional “handover” process from designer to contractor to owner/operator once a design is complete.

Currently, the green building industry is promoting involvement of the architect and engineer in commissioning of a newly constructed or renovated building, a process whereby the building is verified to operate as designed. The concept of flexible, or options-based, design suggests that the “commissioning” process lasts throughout a project’s lifetime, or at least until the option is exercised. Responsibility for overseeing the conditions that implore exercise will lie in the hands of the system operator, such as a building manager (of either the owner or tenant). Thus, it is necessary for knowledge of flexibility to be passed onto building managers throughout the building’s lifetime. A control strategy must be in place for monitoring the need to exercise an option. The results of the real options analyses include rules and indicators for exercise.

If it becomes valuable to exercise an option, the project managers draw upon the design records to inform the conversion. It is beneficial to both designers and owners to compare exercise results to original design intent. This requires collecting relevant data about the conversion or installation, including materials and costs (both anticipated and unanticipated). Comparison of the actual changes to the intent of the original design will help to inform ongoing efforts to strategically use flexibility in system design.

3.7. Chapter conclusion

A real options framework for design is applicable when the object of design will be subject to uncertainty in its future operation or operating environment. The approach provides a framework for 1) identifying future uncertainty during the design phase, 2) defining potentially valuable elements of design flexibility to address the uncertainty during the object’s operational life, 3) evaluating the value of flexibility, and 4) using the assessment for decision-making. The fifth (5) step is to actively manage the flexibility during the project’s lifetime. Thus, the real options framework reinforces the importance of team formation and goal setting within a conventional, and ideally sustainable, design process. It is essential to establish the agreement that flexibility will be actively managed

during the project's lifetime if flexible design and assessment of the value of flexibility are to provide meaningful contributions to a project.

By understanding the uncertainties that will affect the performance of the system, flexibility can be defined so as to a) reduce risk and b) take advantage of possible upside opportunities. Uncertainties can be classified into five risk classes: market, technological, climate, future use, and regulatory. If the major source of risk is a market variable, then financial or hybrid financial-simulation methodologies are appropriate for evaluating the value of flexibility. However, if the source of risk is from a non-market uncertainty or multiple uncertainties, then simulation models are required; use of a financial options model cannot be justified. In particular, if exercise of the real option depends on the physical performance of the system under uncertainty, then an engineering model of the system is needed within the simulation. The following chapters present options-based designs that required a hybrid financial-simulation model (Chapter 4) and a simulation model with a model of physical system performance (Chapter 5).

4. Flexibility in Space-use

The first of two real options cases developed for flexibility in building design is for flexibility in space-use. The real options valuation is based on a financial options model to which simulation capabilities are added. Thorough discussion is given to the assumptions required to validate use of a financial-type model. The model is developed to value the option to convert a space to *office* space under various timing and scale scenarios. It is argued that the model is limited to use for options on space-types that exist in a competitive, relatively liquid market, such as office space in urban areas. Results are presented for the mean, or average, option value for a scenario. Additionally, full probability distributions of some results are given to demonstrate the full spectrum of outcomes that may occur when a design includes an option. Graphics of the full distribution of results help decision-makers see the potential of the option in worst-case and best-case scenarios, as well as those in between.

Model development was initiated out of a case study partnership with the facilities managers for the North American headquarters of a major corporation in the energy business. The company's operations include engineering, science, energy trading, and marketing. As part of a company-wide effort to improve the environmental and sustainable performance of its operations, the facilities officers intend to incorporate green design principles in new buildings and renovation projects. The company views flexible design as having positive impact on sustainability goals because of the opportunity to reduce the throughput of materials, as was discussed in Chapter 1. Numbers relevant to the case study are used as inputs to the models that are developed in this chapter. Gathering of data is discussed in reference to this company to provide an example of the type of efforts needed to conduct a real options valuation of architectural flexibility. Throughout the remainder of this chapter, references are made to how the organization applied the real options approach presented in the previous chapter.

4.1. Identify uncertainties and define flexibility

At the case study company, space-type changes follow from changes in business needs. People are moved as businesses reorganize and redefine operational pursuits. Renovations are generally driven by business needs (i.e., use looking for a space), as opposed to being driven by an empty space looking for a use. A common change that has occurred in the past and that is expected to continue in the future is conversion of many types of space into *office* space. Laboratories have been converted to office space, and office spaces are commonly renovated to accommodate differing business group needs. Most recently, this has meant converting closed, individual offices into open-plan offices; however, it is noted that this trend may reverse or change course to a not-yet imagined office-type in the future.

The company is currently at the conceptual design stage for a new laboratory building. Based on uncertainties in future business needs, they identified the flexibility to convert laboratory space to office space as a design goal. The definition is further refined as a macro-type option, meaning the conversion to office space will happen once or a few times over the lifetime of the building.

4.2. Development of ROs model

If a company determines that it needs (more of) a certain type of space, it may choose among a) renovating an existing space, b) leasing space on the market, or c) building a new facility. The costs of the first two choices are incremental while the cost of the third choice (constructing a new building) is a major investment. Thus, renovation and leasing are further considered herein as alternatives for obtaining office space.

For the option to convert, or renovate, to office space, the two primary uncertainties are 1) the timing of the space need and 2) the cost of the aforementioned alternative – a market rate lease. A decision tree depicting these uncertainties is shown in Figure 11. Timing corresponds to changes in business needs that result in the desire to convert some or all of a space to office space. By framing the renovation question as a question of space *need*, the company has a choice between a) renting office space on the market and

b) renovating existing (unused) corporate space. In doing so, the value of a market-priced lease becomes the underlying asset. The renovation cost, which is a function of the original architectural design and assumed to be a known constant, is the strike price. So long as such space is available on and priced by the market and the company is theoretically indifferent between leased or owned space, a financial options model may be used to value the flexibility.

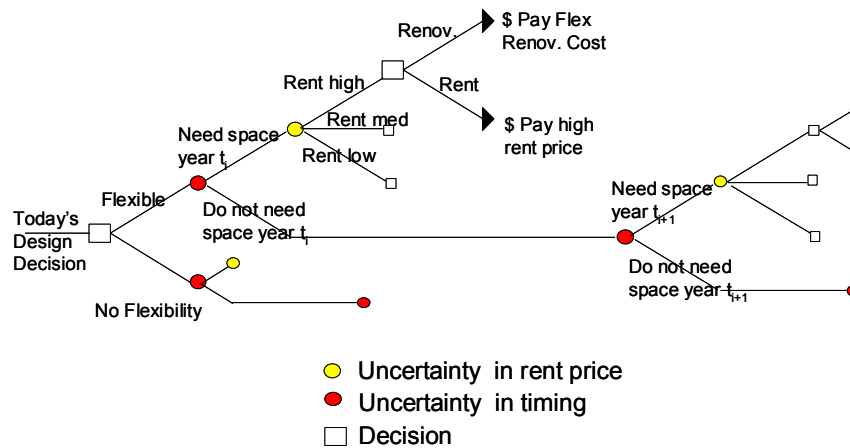


Figure 11. Partial decision tree representing the choices of flexible/inflexible design and renovating/renting with uncertainties in timing of space need and rental (lease) price.

Table 5 gives a guide to real options terminology in the context of architectural flexibility. Ownership of a flexible space is analogous to a financial option. The new type of space is like the share of stock, or underlying asset, that would be obtained by exercising, or paying the strike price (i.e., renovation cost). Owning an option to convert a space implies investment in initial design and construction of a flexible space.

Table 5. Real Options Terminology

Real options terminology...	as applied to options to convert a space.
Underlying asset	New type of space (value of)
Volatility	Uncertainty in the value of the new type of space
Exercise date	Date at which space need occurs
Strike price	Renovation cost (to convert to the new type of space)
Option value	Investment in flexibility (design and construction)

For real estate, options on the future market rate of rent may be valued with financial options methodologies when there exists a well-functioning, liquid market for the type of space. For example, consider the difference between office buildings and laboratory buildings. While many urban and suburban areas have dynamic markets for office space, the same argument is difficult to make for specialized buildings such as laboratories. Laboratory space is a specialized type of real estate, and is thus less liquid than office space. Prices would not be characterized as following a random walk, and prices would include significant, individualized interior build-out costs. Thus, for lack of a complete market, it is generally not appropriate to value an option to convert to laboratory space with financial options theory. Nonetheless, the concept of value in flexibility implies that a design should consider the possibility to convert to other types of space in the future. When the possibility for multiple conversions (at similar renovation costs) exists, the option value for a single conversion becomes a lower bound on the overall value of flexibility.

In reality, the case study company's corporate facility officers have a distinct preference for using on-campus space for a variety of reasons, including security and productivity due to proximity. However, by assuming indifference, the valuation is grounded to a market-based value. At the company, market-based values are used for charging internal rents to business units using office space, so it is a natural extension of this on-going practice. The company also holds several leases for office space in the nearby area. Furthermore, this suburban region has a well-functioning market for office space leases. Negotiation is sometimes possible for agreeing on the final price, but average prices for

different classes of office space are tracked and available. Historical data covering many years or decades is available from consulting firms. These factors justify the existence of an applicable market for office space as the underlying asset.

Just as it is difficult to justify application of financial type options models to options on laboratory and other specialized space at the macro-level, it is similarly difficult to justify their application to valuation of options at the operational level, such as to change *activities* within a space. Changes of activity are governed by uncertainties in business activities and objectives, which, in turn, are determined by expectations in revenues. Because of the many factors contributing to stock price, it is difficult to correlate the price of a company's stock or other market-determined price with specific activities within a company. This is similar to the example of a copper mine, for which there is debate as to whether or not the (randomly fluctuating) price of copper is the correct underlying asset to use to value the option to develop a mine. Simulation (real options) methods may be applicable to options to change activities within a space, and further research is needed in this area. A major part of such research would be to identify the appropriate underlying asset(s). For example, although revenue expectations may be simulated, it would be difficult to directly correlate revenues with the specific activities that produce those revenues.

4.3. Model description – binomial lattice with simulation

Real options valuation aims to inform the level of investment in flexibility. The models presented herein specifically address the question:

How much is it worth to invest in a space that could be renovated to office space for a specified renovation cost in the future?

First a base case model is described. Second, a variation of the model that considers uncertainty in the amount of space that may be needed is presented. Third, another variation of the model is described, which considers the possibility of reverting the space back to its original use. Fourth, a compound, two-time period model is presented, in which the decision in the first period depends on the expected value of the option if left alive for the second time period.

4.3.1. Base case model

The ‘base case’ model covers the two primary uncertainties for the option to convert to office space: 1) the cost of the alternative (i.e., a market rate lease to rent office space) and 2) the timing of the space need. By framing the renovation question as one of space *need*, the exercise date decision is the economically rational choice between the price of a lease and the cost of renovating. The value of a market-priced lease is the underlying asset. Appendix A gives the spreadsheet implementation of the model.

A binomial lattice, which is a financial-type real options model, is used to model uncertainty in the value of the lease and calculate the value of the option. Monte Carlo simulation is used to randomly choose the date of the space need. The model is implemented in a spreadsheet using Monte Carlo analysis software. On the exercise date, the decision-maker compares the price of a lease to the cost of renovating. The option to renovate is exercised if the renovation cost is less than the lease price. The option value is therefore defined as the savings from not paying for the lease, or zero if the lease is less expensive.

Flexibility is a function of the original architectural design, and a range of renovation cost scenarios is used to represent various levels of flexibility. A low renovation cost represents a highly flexible, easy to change space, while a high cost represents a less-flexible, more intensive change scenario. For example, an office space with a moveable wall system has a low renovation cost to convert to a new office configuration. An inflexible design consisting of enclosed rooms constructed of cinder block or stud walls and sheetrock would have a higher cost of renovating to achieve a different configuration.

Assuming a lognormal distribution of possible future rent prices, the binomial lattice parameters are specified to model geometric changes in price. Each node of the binomial lattice, shown in Figure 12, represents a possible value of the price of rent S at that particular point in time. Starting at the current time, the possible values in the next time step Δt are determined by multiplying the previous node’s value of S by the size of the up

u or down d movement, which are calculated from the historical estimate of volatility σ in the lease price as follows (Copeland and Antikarov, 2001; Cox et al., 1979)³:

$$u = e^{\sqrt{\sigma\Delta t}} \quad (4.1)$$

$$d = 1/u \quad (4.2)$$

With a sufficient number of branches in the node for rental price uncertainty, the decision tree in Figure 11 could accomplish a similar model of rent price evolution. However, the recombining property of the binomial lattice means that it grows linearly with the number of time steps, which is a useful property for computational efficiency.

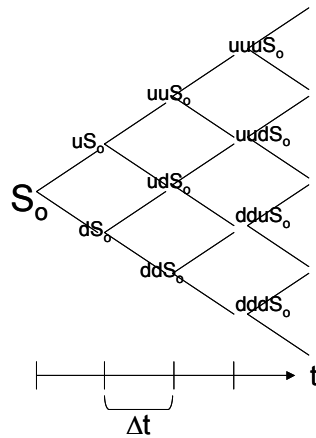


Figure 12. A binomial lattice is used to model a geometric Brownian motion (GBM) evolution of rent price (S).

Whereas the binomial lattice represents the price of renting *per year*, the actual underlying asset should represent the full price of a lease, which is typically more than one year. According to the case study partner, a typical lease term is five years. To calculate the present value of a multi-year lease, the continuously compounded present value factor (P_{lease}) is used,

$$P_{lease} = (1 - e^{-rI}) r^{-1} \quad (4.3)$$

³ Note that a growth rate (i.e. trend or expected rate of return) (α) of the underlying asset could be modeled with the binomial lattice by setting $u = e^{\alpha\Delta t + \sqrt{\sigma\Delta t}}$ and $d = e^{\alpha\Delta t - \sqrt{\sigma\Delta t}}$. However, because the growth rate does not affect the value of the option, as it is conceptually replaced by the risk-free rate of return, it is common practice to leave it out of the model.

where r is an estimated annual discount rate, and l is the length of the lease in years. The price of a lease at any time (S_{lease}), assuming l -years of constant rent payments (S_t) is then calculated as

$$S_{lease, t} = P_{lease} S_t \quad (4.4)$$

A second binomial-lattice is used to determine the option value. As shown in Figure 13, the second lattice uses the corresponding node values of the first lattice to make the exercise decision. The option to renovate is exercised if the cost of renovating X is less than the cost of renting ($S_{lease,t}$). The value of the option to renovate is the savings ($S_{lease,t}-X$) enjoyed by not having to rent. Alternatively, if renting is cheaper than renovating, then the value of the option is zero, and the company would choose to rent office space rather than renovate its own space. It is assumed that the vacant space (that was not renovated) does not generate income. Thus, the decision rule for each node at the exercise date is

$$\min [\text{renovate } (X), \text{rent } (S_{lease, t})] \quad (4.5)$$

which corresponds to

$$\begin{aligned} & \max [\text{savings of renovating v. renting}, 0] \\ & = \max [(S_{lease, t} - X), 0] \end{aligned} \quad (4.6)$$

After the decision rule is applied to each node at the exercise date, the option value (C) is determined by rolling back the lattice using the risk-neutral probability (q), a factor based on the risk-free rate of return (r_f) and the up and down movements in the underlying asset (u, d):

$$q = (1+r_f-d)/(u-d) \quad (4.7)$$

The risk-neutral probability (q) is derived by constructing a replicating portfolio, as demonstrated in Chapter 2.

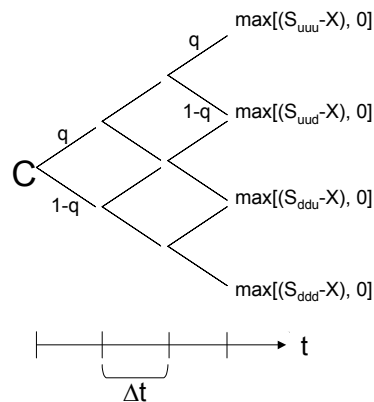


Figure 13. A second binomial lattice is used to calculate the value of the option to renovate.

The uncertainty in the timing of the space need is modeled as a stochastic variable using Monte Carlo simulation. A probability distribution function (PDF) is needed to describe the possible outcomes of the timing variable. PDFs may be derived from historical values, expert opinion, or from a known mathematical model. It is assumed that all probability distributions in the models presented herein are independent.

During each run of the Monte Carlo simulation in the ‘base case’ model, a time (t) is randomly chosen from the defined probability distribution. The first binomial lattice provides the possible random-walk evolutions of rent price up to that chosen time. The option value is calculated using the second binomial lattice model, the Monte Carlo chosen value of time, the prespecified renovation cost, and the corresponding nodes for possible rent-prices from the first binomial lattice. This is repeated for 10,000 trials. The mean of the resulting distribution is the option value for that scenario. A summary of the steps of running the base model is illustrated in Figure 14.

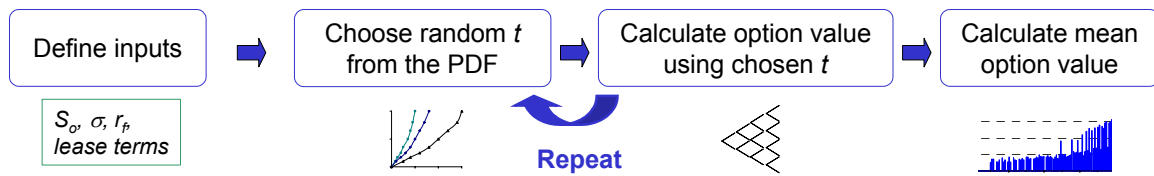


Figure 14. Steps in running the ‘base case’ model. The Monte Carlo simulation chooses the exercise date (t) and the binomial lattice calculates the option value.

4.3.2. Uncertainty in amount of space

The amount of space that may be needed on the exercise date will not necessarily be one hundred percent, as is assumed in the ‘base case’ model. If not all of the space will potentially be needed for renovation, then it may be optimal to design only a percentage of the overall space for flexibility, as shown in Figure 15. The ‘uncertainty in amount of space’ variation of the model helps provide insight on the percentage of space that should be designed with flexibility so as to meet evolving needs.

Three additional inputs are added to the ‘base case’ model to create the ‘uncertainty in amount of space’ model. First, uncertainty in the percentage (χ) of the overall space that may be needed for conversion (to office space) in the future is modeled using an assumed probability distribution and Monte Carlo simulation. It is assumed that the probability distributions on timing (t) and amount (χ) are independent. Second, an input variable (a) is added so that the user can define the amount of space to be made flexible. Third, to distinguish inflexible space from flexible space, a high renovation cost ($X_{inflexible}$) is assigned to the inflexible space. Appendix B provides a discussion of the logic for the ‘uncertainty in amount of space’ model.

Random values for the timing and amount of space needed are chosen in each of the 10,000 Monte Carlo trials. It is assumed that the entire space need must be met either by renting or by renovating. This may be an overly conservative assumption, but it supplies one limiting scenario. The cost of renting is compared to renovating, where the latter may consist of renovating part of the inflexible space if more than the designated amount of flexible space is needed (i.e., if χ is greater than a .) In this version of the model,

flexible space may go unused if there is not sufficient space to meet the entire need, and renovating part of the inflexible space proves to be too expensive as compared to renting. The objective of the model is to determine the option value per unit of designated flexible space. The results help decision-makers balance the *amount* of flexible space with the *level* of flexibility.

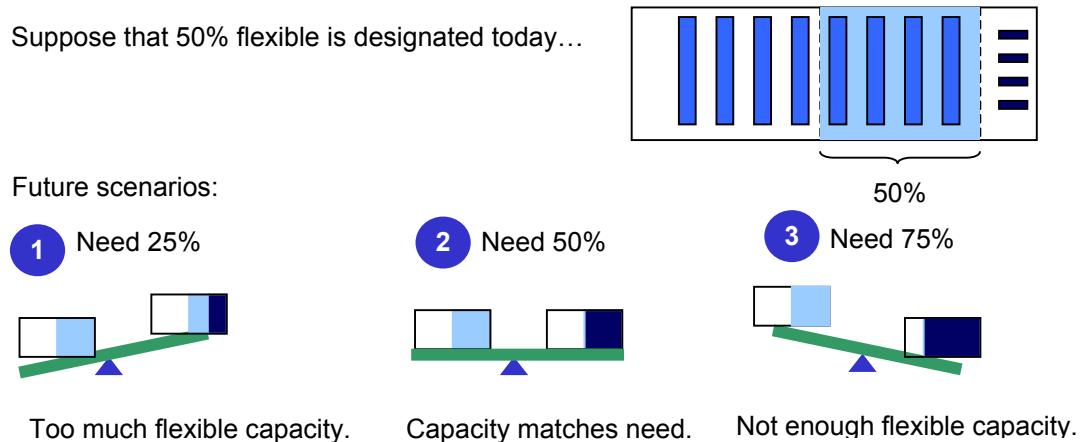


Figure 15. The optimal amount of space to allocate as flexible depends on the future need.

4.3.3. Possibility of reversion

The second variation of the ‘base case’ model considers the possibility that the space might undergo multiple conversions. Because of the limitation of the binomial lattice model to consider the value of options to convert to *office-type* space, the possibility of multiple conversions is narrowed to the specific case where the space is converted to *office* space and then reconverted to the *original* type of space at a later date. For example, in the design of a new laboratory space at the case study company, the decision-makers are interested in the value of being able to change the space to office space at some future time and then back to laboratory space further in the future.

Thus, in the ‘possibility of reversion’ model, the option is defined as the right to convert to office space at some future time and then back to the *original* (specialized) space type at a later date. This rather restrictive definition of the option is employed because of the

rationale that financial-type options models, such as the binomial lattice, are only appropriate for an underlying asset priced in a sufficiently dynamic market, such as office-type space in urban areas. By requiring that the space be reverted to the original type of space after a renovation to office space, the option can be compared to the case where office space is leased for the interim period, thereby leaving the original space intact and ready for use at the future date.⁴ The underlying asset is the stochastic price of the office space lease for the interim period $(t_2 - t_1)$, and the strike price is the combined renovation costs of converting to office space at t_1 and back to the original space at t_2 , discounted to t_1 .

Hence, the option value in the ‘possibility of reversion’ model is defined as the savings of renovating to office-space at t_1 and then back to the original (specialized) type of space at t_2 versus leasing office space for the duration of the time period $(t_2 - t_1)$,

$$\max [(S_{lease, t_1} - X_1 - X_2), 0] \quad (4.8)$$

where S_{lease, t_1} is the value of an office-space lease at t_1 with a contract duration of $(t_2 - t_1)$, X_1 is the office renovation cost at t_1 , and X_2 is the reversion renovation cost at t_2 (discounted to t_1). It is assumed that the condition of the original space is exactly the same at t_1 and t_2 , no matter if it was renovated to office space and back again or simply left vacant. No alternative income generating use is considered for the otherwise vacant space if office space is leased for the intermediate time period. This variation of the base case model requires probability distributions for two exercise dates, which are assumed to be independent. Monte Carlo simulation is used to draw the random exercise dates (t_1 and t_2). The value of $(t_2 - t_1)$ is used as l in Eq. 4.3 to calculate the present value factor for a lease of $(t_2 - t_1)$ years in length. The value of the lease (S_{lease, t_1}) is calculated according to Eq. 4.4 using the t_1 nodes of the binomial lattice for office-space price as S_{t_1} . Inputs for two strike prices are also needed, one for the cost of renovating to office space and one for the cost of reverting to the original space type.

⁴ This formulation is distinct from a switch option, which is defined as the exchange of one asset for a more valuable asset.

4.3.4. Two-period (compound option value)

If a space is not renovated, because the decision was made to lease instead, the owner is left with unused space. However, this unused, flexible space is an asset since it could potentially be renovated in a second time period. The base case model only considered the option value from one possible exercise date, and the exercise date decision only assessed the current economics of leasing versus renovating. In this section, the base case model is expanded to add a second possible exercise date. Furthermore, the first-exercise date decision takes into account an added component – the option value in leaving the flexible space “unused” so that it could possibly be renovated at a later date. This formulation of the problem statement is distinct from the case in which renovation of the same space can occur twice and the two renovations are independent of each other; in that case, the option values of the two time periods are independent and additive. However, by formulating the problem such that exercise in the second time period can only occur if it did not occur in the first time period, the model represents a case in which facilities managers are aware of another *possible* future need for the space that they would like to take into account in deciding whether or not to use it for the more immediate need.

The logic for the two-period compound sequential model is shown using the decision tree of Figure 16. Instead of simply assuring that renovating is less expensive than leasing to make the first period decision, as shown in the “additive” illustration in Figure 16, the potential savings must be compared to the option value of possibly being able to renovate an unused space during the second time period. The value of the option in the first period depends on the value of keeping the option alive for possible exercise in the second period; this is known as a *compound* option (Copeland and Antikarov, 2001).

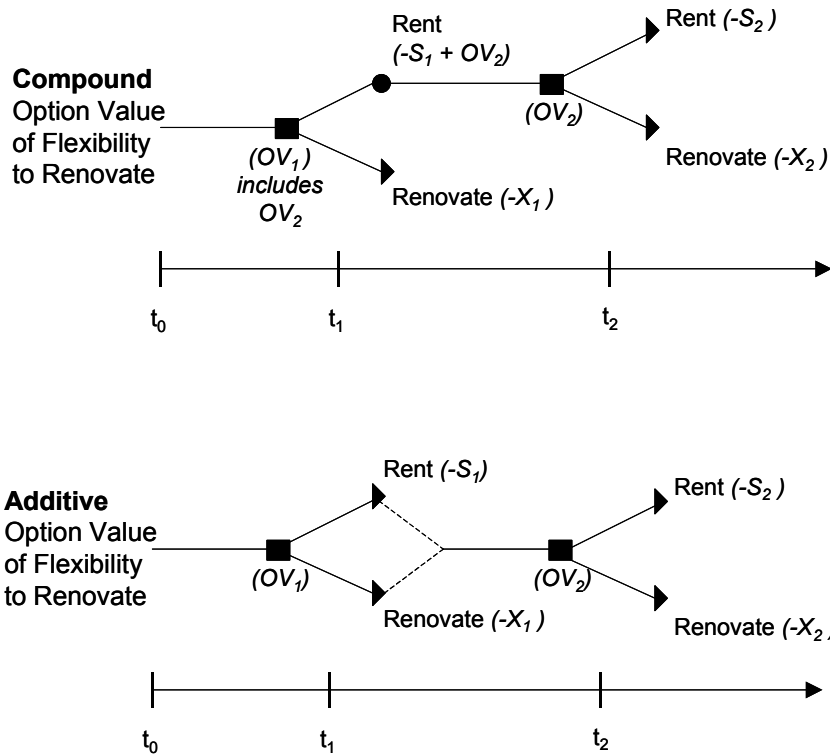


Figure 16. The top figure illustrates the compound two-period model and the dependence of the first period decision on the probabilistic outcome of the second period decision. The bottom figure, in contrast, is provided to represent an additive formulation of the model.

The vocabulary introduced for the compound two-period model developed specifically for this case is given in Table 6. The model developed herein to calculate this compound option value involves three *option trees* and two *event trees*:

- *(Fundamental) Event Tree*, which describes evolution of the rent prices,
- *1st Option Tree*, which calculates the first period option value (C_1) based on the value of renovating versus leaving the option open for the second period (as given by the Imaginary 2nd Option Tree)
- *Imaginary 2nd Option Tree*, which ignores the presence of a first period option and calculates second period option values at each node given T_2
- *Truncated Event Tree*, which starts at T_1 and includes only the states of nature for which exercise (renovation) did not occur at the end of the first time period, and

- *2nd Option Tree*, which calculates the true second period option value (C_2) based on the Truncated Event Tree.

The sum of the first and second period option values (C_1 and C_2) is the compound option value of a space that can (possibly) be renovated in two sequential time periods for a specified cost per square foot. An illustration of the compound model and further description are given in Appendix C. Results will be given for the compound two-period model as well as for the additive scenario to demonstrate the difference in the two ways of viewing the problem.

Table 6. Vocabulary for the compound two-period model.

C_1	option value in first time period
C_2	option value in second time period
X_1	strike price in first time period
X_2	strike price in second time period
T_1	exercise date (end date) of first time period
T_2	exercise date (end date) of second time period

4.4. Results

Results will vary as to the uniqueness of each organizational situation; thus, the discussion and results presented in these sections are meant to provide lessons for future application of the model to other corporate real estate and development situations. The inputs for which results are presented are based on the case study corporation. The inputs represent the office market in their geographical area and their estimates for other uncertain variables. First, the inputs and results for the base case model are presented. Then, the additional inputs for each of the three variations of the base case model are presented along with their results.

4.4.1. Validation of base case

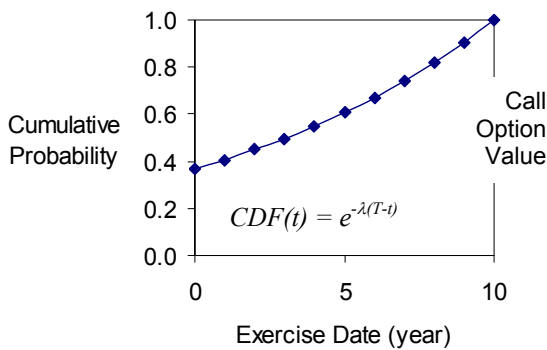
The model is validated using a closed-form solution for an option that can only be exercised on the exercise date (i.e., European-type option) where that exercise date is stochastic. Jennergren and Naslund (1996) derived a closed-form solution for a European-type call option with a stochastic expiration date, where the probability

distribution function of the exercise date t is a two-parameter exponential distribution described by parameters λ and T ,

$$CDF(t) = e^{-\lambda(T-t)} \quad (4.9)$$

The variable T is the maximum time horizon (until expiration) and the parameter λ is set equal to the inverse of T for deriving the closed-form solution. A 10-year maximum time horizon yields the exponential CDF pictured in panel A of Figure 17. Note that there is a finite probability (0.37) that the option is exercised at time zero with this form of the exponential distribution. The Jennergren-Naslund formula gives an option value of \$17.85 using the following inputs: λ (0.1 years^{-1}), r_f ($10\%/year$), T (10 years), S ($\$39.35$), X ($\50), and σ ($0.3935/year$).

A. (2-parameter) exponential cumulative probability distribution of exercise date.



B. European call option value assuming stochastic exercise date described by PDF in (A).

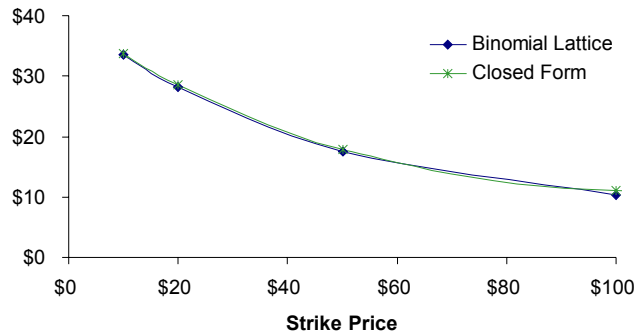


Figure 17. A closed-form solution, based on the cumulative distribution function shown in panel (A) was used to validate the model (panel B).

Using the same exponential PDF and other input parameters in the binomial lattice-Monte Carlo simulation model, the result is a mean option value of \$17.50, or 2.0 percent less than the closed-form solution. For a strike price (X) of \$10, the closed-form solution yields an option value of \$33.70 and the model gives a mean value of \$33.47, or 0.7 percent less than the closed-form solution. Results for a range of strike prices are shown

in panel B of Figure 17. The binomial lattice model shows excellent agreement with the closed-form solution. The advantage of the model over the closed-form solution is that it can accommodate any type of PDF on the timing of the space need, not only a two-parameter exponential distribution with $\lambda = 1/T$. A unique description of a PDF is presented in the following case study.

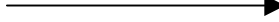
4.4.2. *Base case*

The inputs for the base case model and the assumed values applicable to the corporate case study are given in Table 7. The basic model inputs are current annual rent for office space per square foot (SF), standard deviation of rental prices, the risk-free rate of return, length of a lease, discount rate for lease payments, and a probability distribution of the exercise date. To represent a range of flexibility scenarios, renovation costs of \$25/SF, \$50/SF, and \$125/SF, or ratios of 1:1, 2:1, and 5:1 of renovation cost to current annual rent price, were chosen.⁵

The current market value of office rent (S_0) of \$25/SF/year is estimated from current leases held by the case study company and from statistics published by consulting firms that monitor the relevant geographic market (Cushman & Wakefield, 2003; CB Richard Ellis, 2003). The annual rent translates to \$98.37/SF as the present value of a 5-year lease, discounted continuously at an annual rate of 10 percent. An estimate of the volatility is used, and a sensitivity analysis showed that the option value is not highly sensitive to volatility. The risk-free rate of return is the rate of return on 10-year U.S. Treasury Bills in January 2004. The 10-year value was chosen because it is the closest time period to the assumed time horizon in this case; however, the values did not vary significantly across other T-Bill time horizons.

⁵ To gauge the cost of renovating, the case study partner provided recent figures for renovation costs in two cases: a) office space to new office space (\$30-40/SF), and b) laboratory to office space (\$300/SF).

Table 7. Input Parameters for Base Case Model: example values developed from corporate case study.

Variable	Options Language	Description	Case Study Input Value
S_o	Underlying asset	Initial rental price of office space	\$25/SF/year (current lease price is \$98/SF for l and r specified below)
σ	Volatility (of underlying asset)	Annual volatility of market rental prices	0.10/year (0.39/year for lease specified by values of l and r below)
X	Strike price	Renovation Cost	\$25/SF, \$50/SF, and \$125/SF  <i>Decreasing Flexibility</i>
t	Exercise date	Likelihood of timing of renovation (space need)	See CDFs in Figure 18
r_f	Risk free rate of return		5%/year
l	Length of lease		5 years
r	Rate for discounting lease payments to value at time of signing lease		10%/year

The estimated probability distributions for the exercise date at the case study company are shown in Figure 18. The distribution labeled “8-yr. horizon” represents the consensus-based estimate of three facilities managers at the case study company. The group specifically thought in terms of renovations to office space. They estimate that an area equal to the total square footage of a typical building on their campus will be renovated over the next eight years according to the cumulative probability distribution function (CDF) labeled ‘8 yr. horizon’ in Figure 18. Three specific data points were cited, as shown by the marked data points in Figure 18: 25 percent of the space is expected to be renovated by the third year, 50 percent by the fifth year, and 100 percent by the eighth year. Intermediate data points were fit to produce the exponential shaped curve. These data points can be interpreted as the cumulative probability of a space need occurring by a certain time. There is a 50 percent probability that a space need occurs within five years and a 100 percent probability that it occurs within eight years. The mean time of a space need is 4.65 years in the 8-year time horizon.

For sensitivity analysis, two other probability distributions were also modeled. One represents a maximum time horizon of 5-years and another represents 15-years. The same shape of the 8-year CDF was maintained in the other distributions. In the 5-year time horizon CDF, there is a fifty-percent cumulative probability that the space-need will arise by year 3.5. The fifty-percent cumulative probability rises to year 10 for the 15-year case.

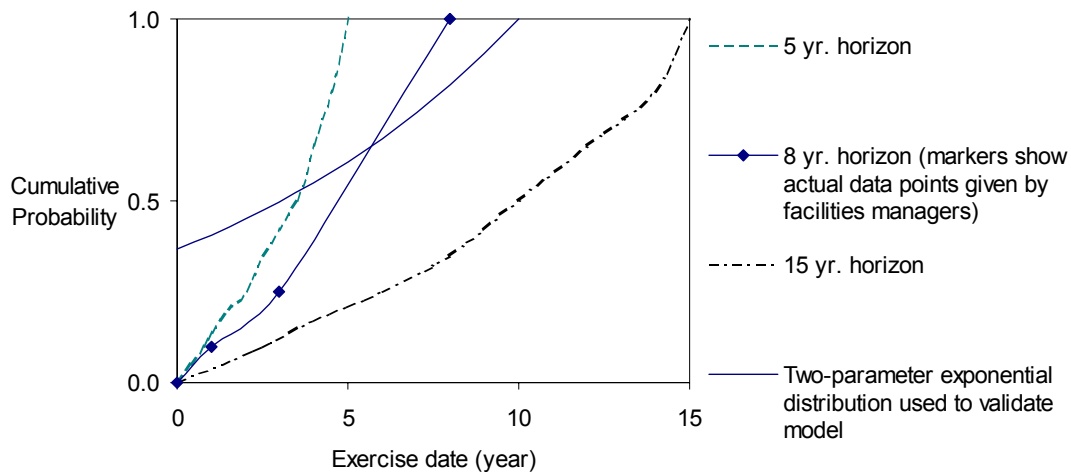


Figure 18. Three estimates of the probability distribution of the timing of office space needs at the case study partner company, shown with the two-parameter exponential distribution used to validate the model. The data points marked in the “8-yr. horizon” distribution are the actual data points estimated by the case study company’s facilities managers.

Using these inputs, the mean option value of the flexibility to convert a space to office space at strike prices (renovation costs) of \$25, \$50, and \$125/SF for the three time horizons is shown in Figure 19. The results are interpreted as follows:

In the 8-year time horizon scenario, a design that can be renovated for \$25/SF should cost no more, on average, than \$79/SF in design and construction expense above and beyond a baseline, inflexible (i.e., very high renovation cost) design.

If that inflexible architecture is represented by the \$125/SF renovation cost case, which has a mean option value of \$31/SF, then the *extra amount* to invest in flexible design and construction for the \$25/SF renovation cost design is the difference between the two

option value results, or \$48/SF (i.e., \$79-\$31). The option value of a relatively inflexible case reflects the intrinsic value in a building's shell and structure, which are prerequisite to further definition of a building's use. Further discussion of the practical and technical issues of using the option value to aid decision-making is presented in Section 6. General observations and sensitivity analysis are now discussed. Table 9 gives the percentage results of the sensitivity analyses.

Each bar in Figure 19 represents the mean option value of the 10,000 Monte Carlo simulation trials for each scenario. Figure 20 shows the option value frequency distribution for the three renovation cost scenarios under the 8-year time horizon probability distribution. A range of option values is produced in each set of 10,000 trials because the expiration date of the option is chosen randomly in every trial. Notice that the width of the distribution is greater for higher exercise costs. The 10th percentile value, or 90 percent certainty level for the minimum amount of realized savings from the option to renovating (versus renting), is given in Table 8 along with other relevant statistics.

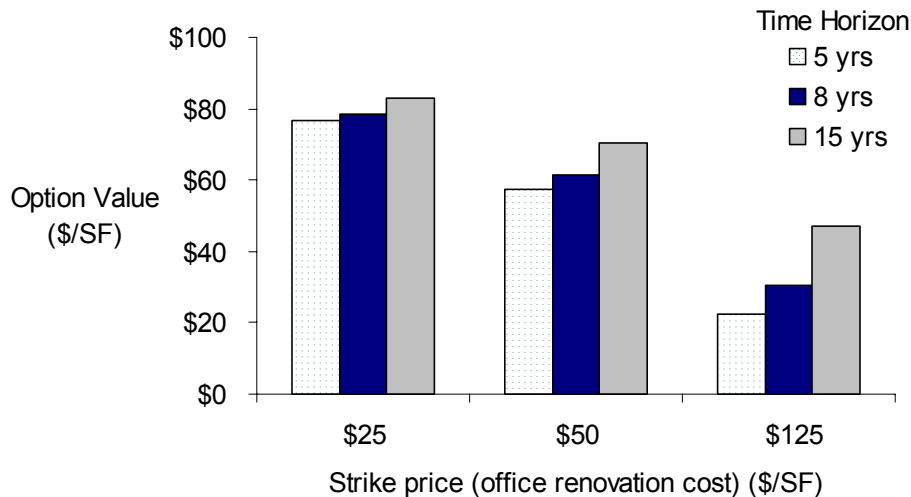


Figure 19. Results of the option value to renovate for 5-, 8-, and 15-year time horizons. The current present value of a 5-year lease is \$98/SF and the volatility of the lease is 0.39/year.

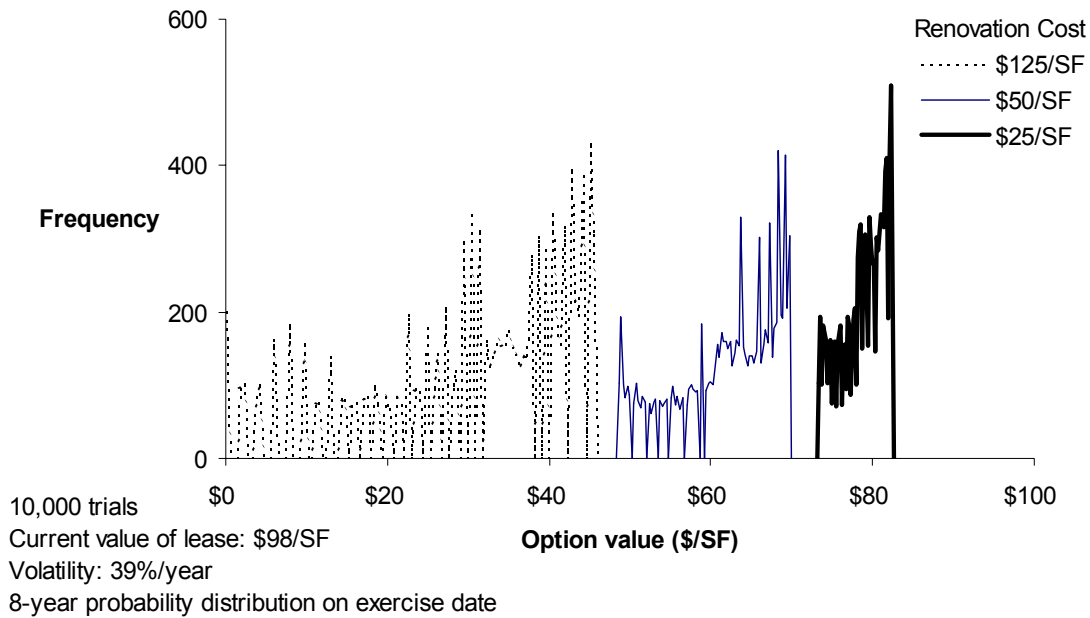


Figure 20. Frequency distribution of base case results for the 8-year time horizon. Table 8 provides statistics for each distribution.

Table 8. Option value (\$/SF) statistics (base case under the 8-year probability distribution)

Option Value (\$/SF) as a function of exercise cost			
Renovation Cost	\$25/SF	\$50/SF	\$125/SF
Minimum	\$0/SF	\$0/SF	\$0/SF
10 th percentile (90% certainty level of minimum option value)	\$75	\$51	\$10
Mean	\$79	\$62	\$31
90 th percentile (shows upside potential)	\$82	\$69	\$44

As with a standard call option, the option value to renovate increases with a longer time horizon. This occurs for the same two reasons that the value of a financial call option increases with increased time to expiration: more time allows for a wider range of possible future rents and the fixed strike price is discounted over a longer time period (Brealey and Myers, 2000). Higher rents translate to greater savings attributable to the option to renovate for a fixed cost. This result holds for all scenarios presented in this chapter. Also as for a standard call option, the option value decreases with increased

renovation cost. Thus, for example, a space that costs \$125/SF to renovate in the future should have less invested in its design and construction than a more flexible space that could be renovated for only \$25/SF in the future.

As seen in Figure 19, the sensitivity of option value to time horizon increases with the strike price. At a highly flexible renovation cost of \$25/SF, the mean option value is not very sensitive to the time horizon, ranging only slightly from \$77/SF to \$83/SF for time horizons of 5 to 15 years respectively. However, at a less flexible renovation cost of \$125/SF, the mean option value has a much wider range: \$22/SF to \$47/SF for time horizons of 5 to 15 years.

The value of the flexibility to renovate is sensitive to the opportunity cost of capital of the lease (r) and the duration of the lease (I). The base case is an r of 10 percent for a five-year lease, which results in an option value of \$79/SF for a \$25/SF strike price (8-year time horizon). Increasing r to 15 percent per year results in a decrease in option value of 13 percent and decreasing the r to 5 percent results in an increase in option value of 16 percent. Changing the duration of the lease from 5 years to 2 years decreases the option value by 68 percent, as the quantity to which the cost of renovation is compared (i.e., the initial lease price) is reduced from \$98/SF to \$45/SF. Applying an inflation factor to the renovation cost (strike price) of 2 percent per year reduces option value slightly (2-10 percent for strike prices of \$25-125/SF).

Table 9. Base Case Mean Option Value Summary of Results and Sensitivity Analysis
(base case option value and percent deviation from base case)

Strike Price (Renovation Cost)	\$25/SF	\$50/SF	\$125/SF
Base Case mean option value for 8-yr time horizon, \$25 S_0 , 0.1 σ , 5-yr lease, 10% r , 5% r_f	\$78.54/SF	\$61.66/SF	\$30.68/SF
5-yr time horizon	-2%	-7%	-27%
15-yr time horizon	6%	14%	53%
0.2 σ	6%	19%	80%
\$20 S_0	-22%	-24%	-28%
\$30 S_0	17%	15%	8%
5% r for lease	16%	--	--
15% r for lease	-13%	--	--
Annual inflation of 2% in renovation costs	-2%	-4%	-10%

4.4.3. Black-Scholes formula approximated result

With small enough time-steps in the base-case binomial lattice model, the result approaches that given by the Black-Scholes formula (Black and Scholes, 1973), a closed-form solution for the value of an option to purchase an asset on a specified date for a prespecified price. A comparison of the results from the binomial lattice model to the Black-Scholes formula is given in this section, with the objective of determining when the Black-Scholes formula can be used to provide approximations of option value. Given the presence of the Black-Scholes formula on most pocket-financial calculators, guidelines are given for using the formula to make initial, guiding estimates on option value for flexible space in practice.

Development of a combined binomial lattice, simulation model was necessary to describe the features relevant to the case of flexibility in space-use, and only then was it possible to go back to the simplicity of the Black-Scholes formula to check for agreement. For example, the Black-Scholes formula cannot be modified to value a compound option, which is the fourth variation of the model presented for the value of an option to renovate a space. Second, the binomial-lattice model is more intuitive to work with when considering the model variations presented because of its graphical (i.e., branching and recombining) form. It can also be programmed to give the probability of possible

outcomes, and it is more intuitive to describe to a non-mathematical audience. For these reasons, the binomial lattice model was the appropriate starting point for valuing flexibility in space use, as it is in the financial markets for valuing specialized options on financial assets (Johnson, 2004).

Whereas the binomial lattice is a discrete time approximation of a random walk, the Black-Scholes formula assumes continuous movements in the price of the underlying asset as described by Eq.'s 2.12-13 to lead to a closed-form solution. The Black-Scholes formula for the value of a call option C is as follows (Brealey and Myers, 2000):

$$C = N(d_1)S - N(d_2)Xe^{-rt} \quad (4.10)$$

where

$$d_1 = \frac{\ln(S/Xe^{-rt}) + \sigma^2 t / 2}{\sigma \sqrt{t}}$$

$$d_2 = d_1 - \sigma \sqrt{t}$$

$N(d)$ = cumulative normal probability density function, or the probability that a normally distributed random variables will be less than or equal to d , and S , X , r , and t are the current price of underlying asset, the strike price, the risk free discount rate, and the exercise date, respectively, as in the binomial lattice model.

Table 10 shows a comparison of the results from the Black-Scholes formula to those from the Base Case binomial lattice, simulation model using the inputs listed in Table 7, including an initial lease price of \$98/SF with annual volatility of 0.39, and the 8-year time horizon PDF. When each method is combined with Monte Carlo simulation for the exercise date (i.e., randomly drawing the exercise date 10,000 times and calculating the option value for each draw), the mean of the results from the Black-Scholes formula and the binomial lattice model agree for the range of strike prices evaluated (i.e., less than one-percent difference). The slight difference is due to continuous versus discrete approximation of time. However, the useful finding is that use of the expected value of the 8-year time horizon PDF, or 4.7 years, in the Black-Scholes formula provides a result that agrees to an excellent degree with the full binomial lattice-Monte Carlo simulation result for the base case model. Thus, it is shown that, when the shape of the probability

distribution on exercise date is similar to an exponential distribution, the expected value of the distribution can be used in the Black-Scholes formula to approximate option value. It is unknown how the Black-Scholes formula would agree if the probability distribution for the exercise date had a different form.

Table 10. Mean option value (\$/SF) comparison using the Black-Scholes Formula (inputs as in Table 7 and the 8-year time horizon PDF)

Strike Price (Renovation Cost)	\$25/SF	\$50/SF	\$125/SF
Binomial Lattice Base Case Model Result	\$78.54	\$61.66	\$30.68
% difference with Black-Scholes Formula, also calculated with 10,000 trials of a Monte Carlo simulation for exercise date	0.4%	0.3%	-0.4%
% difference with Black-Scholes Formula calculated with a single exercise date: the mean of the 8-year time horizon PDF (4.7 yr.)	0.5%	1.1%	4.8%

The Black-Scholes formula can be used to determine the upper limit on the value of a design that can be renovated to office space. When timing of the date of space need is uncertain, use of the maximum possible date as the exercise date t in the formula yields the maximum value of a call option to renovate a space to office space. For example, using the base case inputs in Table 7 and the maximum of the 8-year time horizon (i.e., 8 years), the Black-Scholes formula gives an option value of \$82/SF for a \$25/SF renovation cost. This is slightly higher (5%) than the mean value of the option (\$79/SF) calculated with the Base Case binomial lattice, simulation model. As renovation cost increases, the upper bound deviates more from the mean value given by the Base Case model; for renovation costs of \$50/SF and \$125/SF, the upper bounds given by this method are 13% and 49% higher than the mean option values from the Base Case model, respectively. Approximation of an upper bound for the value of flexibility, obtained without intensive modeling nor estimation of the shape of the probability distribution on exercise date, may be useful for guiding initial estimates on investment in the flexibility to renovate a space.

For the ‘uncertainty in amount of space’ and ‘possibility of reversion’ models, modifications can also be made to the Black-Scholes formula such that it yields results that agree with the binomial lattice model. However, use of the expected value of the other uncertain variables introduced in these models does not produce results that agree with a Monte Carlo simulation result. For example, for the ‘uncertainty in amount of space’ model, the expected value of future space need does not yield the same result as a simulation that randomly chooses from the uniform distribution of possible value of future space need when the amount of designated flexible space is equal to or greater than the mean value of space needed. The reason is that, in the simulation, it is possible that more space is needed than the amount that is flexible, and option value is reduced in those cases. The Black-Scholes formula can only be used to approximate option value in two cases: a) when 100% of the space is flexible (i.e., all has the same strike price) and b) when the designated amount of flexible space is less than the expected value of space needed. For the ‘possibility of reversion’ scenario, use of the expected values of the exercise dates in the Black-Scholes formula either over or under estimates option value, depending on the time horizon considered, and thus is not a good approximation method.

In summary, the Black-Scholes formula can be used to determine the upper limit on the value of a design that can be renovated to office space (or one-hundred percent space need and flexibility), and it can be used in the base case to a certain degree of satisfaction with the expected value of the exercise date to approximate option value. For the variations of the model, approximation is possible for a limited set of cases in the ‘uncertainty in amount of space’ model, but not in the ‘possibility of reversion’ model.

4.4.4. Uncertainty in amount of space

To consider uncertainty in the amount of space needed, the base case model is modified to include the additional inputs listed in Table 11: a probability distribution for the amount of space needed χ , a design parameter a that represents the amount of flexible space, and the renovation cost of inflexible space $X_{inflexible}$. The model is analyzed for allocated amounts of flexible space of 25%, 50%, 75%, and 100%, where the latter tests the sensitivity of option value to uncertainty in amount of space needed alone. The

assumed cost of renovating inflexible space is \$250/SF, which is of the same order of magnitude as renovation costs from laboratory to office space at the case study company. All other inputs are those listed for the base case model in Table 7.

The assumed probability distributions on the amount of space needed χ in the future are shown in Figure 21. The first is a uniform distribution of zero to one hundred percent, which has an expected value of 50 percent space need. (Note that the base case model assumed that 100 percent of the space would be needed on the exercise date.) A second distribution consisting of uniform probabilities in increments of 25, 50, 75, and 100 percent of the space was also assessed as suggested by the case study partners. The ‘incremental’ distribution has an expected value of 62.5 percent space need. Any desired distribution could be an input to the model, and as the variance in results will illustrate, it is important to communicate this assumption clearly and test a variety of possible distributions deemed relevant to the case at hand.

Table 11. Additional Input Parameters to the Base Case Model (Table 2) for the ‘Uncertainty in Amount of Space’ Model

Variable	Options Language	Description	Case Study Value
χ	---	Amount of space needed on exercise date	See PDF in Figure 21
a	---	Allocated amount of flexible space	25%, 50%, 75%, and 100%
$X_{inflexible}$	Strike price for inflexible space	Renovation cost for inflexible space	\$250/SF

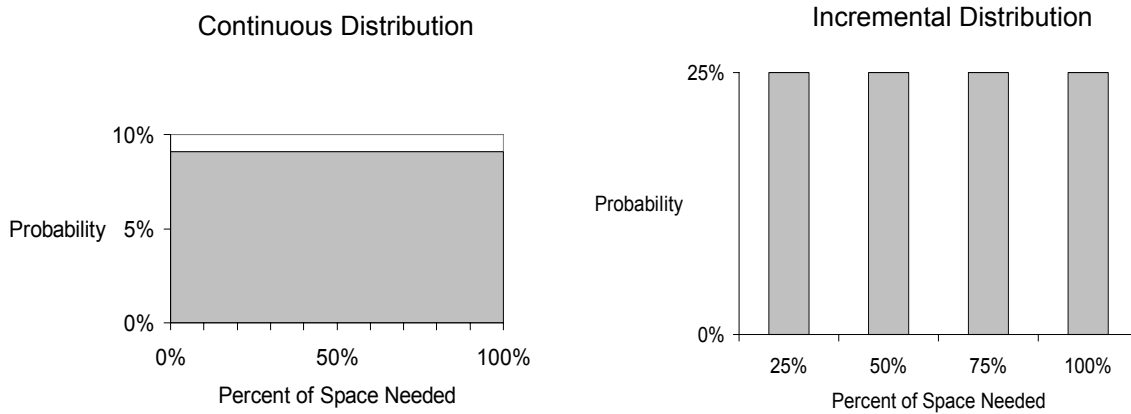


Figure 21. Uniform probability distributions of the percent of space needed.

The results of the ‘uncertainty in amount of space needed’ model are given in Figure 22. Recall that the total cost of renovating may partially consist of the cost of renovating inflexible space (at $X_{inflexible}$ of \$250/SF) if more than the designated amount of flexible space is needed (i.e., if χ is greater than a). (See Appendix B). In this model, the mean option value results are calculated in two ways:

- a. total option value (\$/SF), as before, and
- b. option value per unit of flexible space (\$/SF of flexible space), calculated as the total option value (\$/SF) divided by the parameter a .

The per unit option value provides information on the amount to be invested in the flexible fraction of the design.

The results can be interpreted as follows (8-year time horizon): for a design that can be renovated (to office space) for \$50/SF in the future, no more than \$31/SF should be invested in the design and construction of the flexible space if *all* of it is made flexible; however, if only 50 percent is made flexible, then \$41 can be invested in each square foot of flexible space. Notice that these option values are significantly lower than the results from the base case model. This is due to the lesser amount of space needed, on average,

as compared to the base case scenario, which assumes that all of the space may be needed. Because the amount of space needed χ is defined as a percentage of the overall amount of space, a lower value of χ equates to a decrease in the potential savings from the option to renovate, for 100 percent flexible space.

The results show that mean per unit option value decreases with both increasing amounts of flexible space a and increasing flexible renovation cost X when the amount of space needed is uncertain and the inflexible renovation cost $X_{inflexible}$ is assumed to be \$250/SF. It is characteristic that option value, when in the form of a call option, decreases as strike price increases. The decrease in mean option value with increased amount of flexible space a is partly a result of dilution by normalizing the value to (increasing amounts of) flexible space. The frequency distribution of all 10,000 trials for the 25 and 50 percent allocated flexible space results (Figure 23) shows that, although the *mean per unit* option value for the lesser amount of allocated space is higher than the mean per unit value for the greater amount of allocated space as seen in Figure 22, there is a greater chance of realizing higher *total* option value for the 50 percent flexible space scenario. The statistics of total option value are given in Table 12. The figures in Table 12 show that the upside potential increases as a greater amount of flexible space is provided.

The monotonically decreasing characteristic of the per unit results shown in Figure 22 as a function of flexible renovation costs does not hold when the inflexible renovation cost is increased to \$500/SF (from \$250/SF), as shown in Figure 24. With the higher inflexible strike price, maximum per unit option value occurs at 75 percent flexible space for (flexible) renovation costs of \$25/SF and \$50/SF. This results from the greater penalty, in the form of a higher cost of renovating inflexible space, of not having enough flexible space available when only 25 percent or 50 percent of the space is designated as flexible.

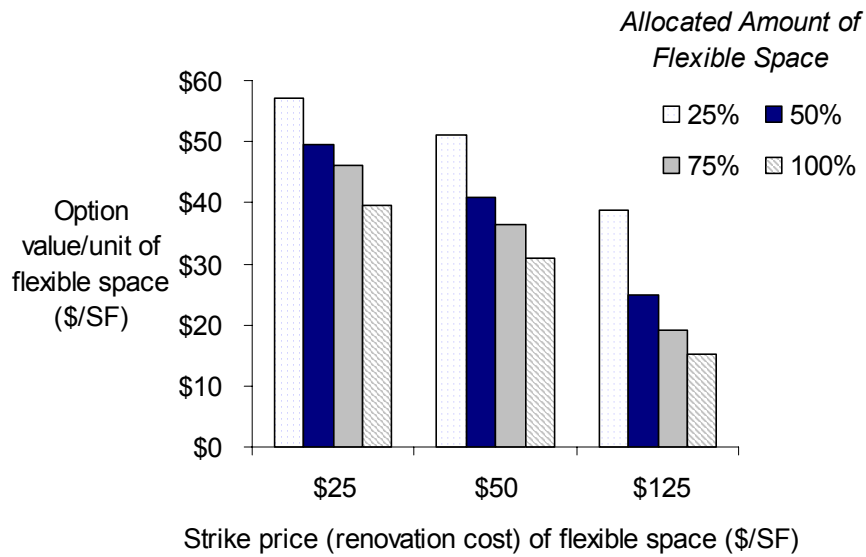


Figure 22. Mean option value results for various levels of flexible renovation costs and allocated (designed) amounts of flexible space for an inflexible renovation cost of \$250/SF. Other inputs include the 8-year time horizon PDF and uniform probability distribution on amount of space needed.

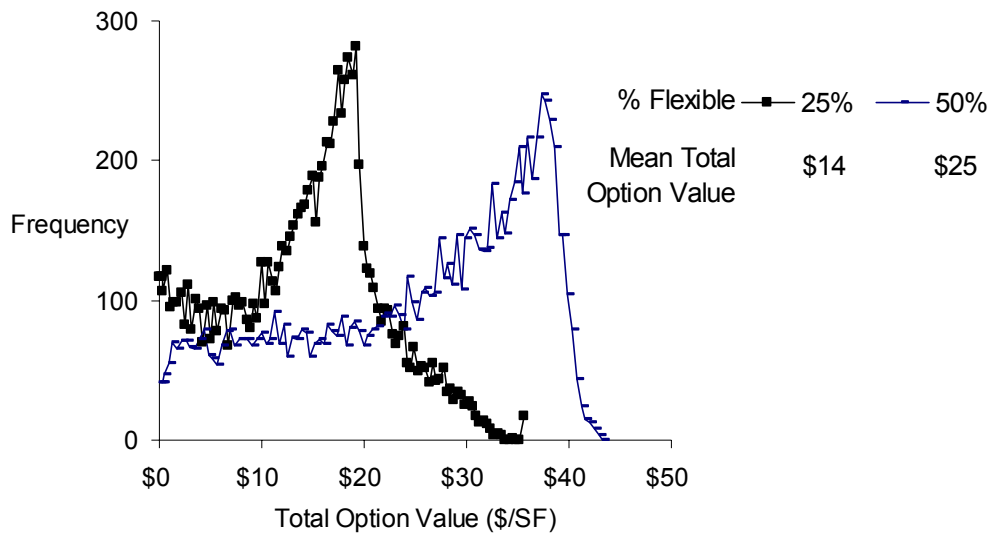


Figure 23. Frequency distribution of total option value for allocated amounts of space of 25 and 50 percent. Flexible renovation cost is \$25/SF, and inflexible renovation cost is \$250/SF.

Table 12. Total option value statistics as a function of amount of flexible space. Flexible renovation cost \$25/SF, inflexible renovation cost \$250/SF.

Total option value (\$/SF) as a function of % flexible space			
% flexible space	25%	50%	75%
Minimum	\$0	\$0	\$0
10 th percentile (90% certainty level of minimum option value)	\$3	\$6	\$7
Mean	\$14	\$25	\$35
90 th percentile (shows upside potential)	\$24	\$38	\$57

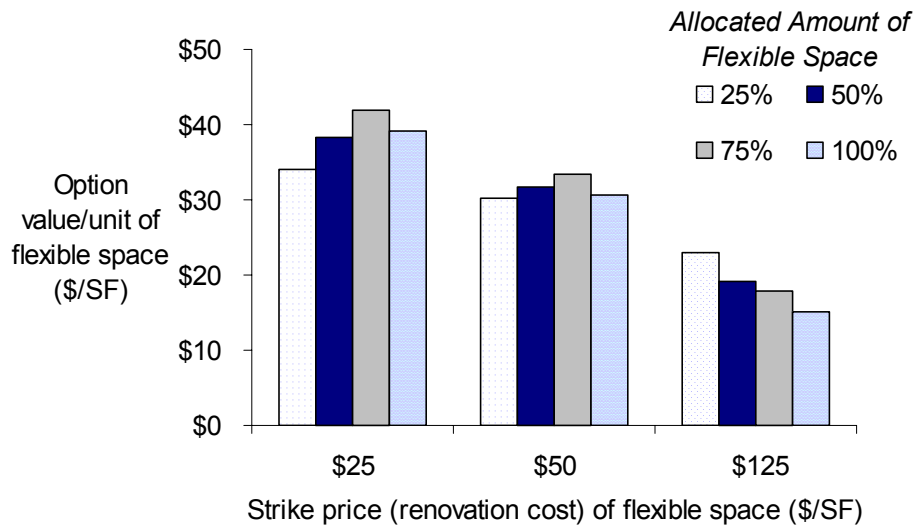


Figure 24. Results as in Figure 22, but with \$500/SF inflexible renovation cost.

Overall, mean option value (per unit of flexible space) decreases when the inflexible renovation cost is increased, and the magnitude of decrease depends on the designated amount of flexible space. Figure 25 compares mean option value results for 50 percent allocated space for inflexible renovation costs of \$250/SF and \$500/SF. Intuitively, the less inflexible space that there is in the scenario, the less impact variation of inflexible renovation cost has on option value. For example, for 75 percent flexible space (i.e., 25 percent inflexible space), the difference in option value is approximately 8 percent when the inflexible renovation cost is increased to \$500/SF from \$250/SF. However, for 25

percent flexible space (i.e., 75 percent inflexible space), the difference in option value is much more pronounced at approximately 41 percent. Note that even inflexibly designed spaces (that cost \$500/SF to renovate to office space) have some inherent option value.

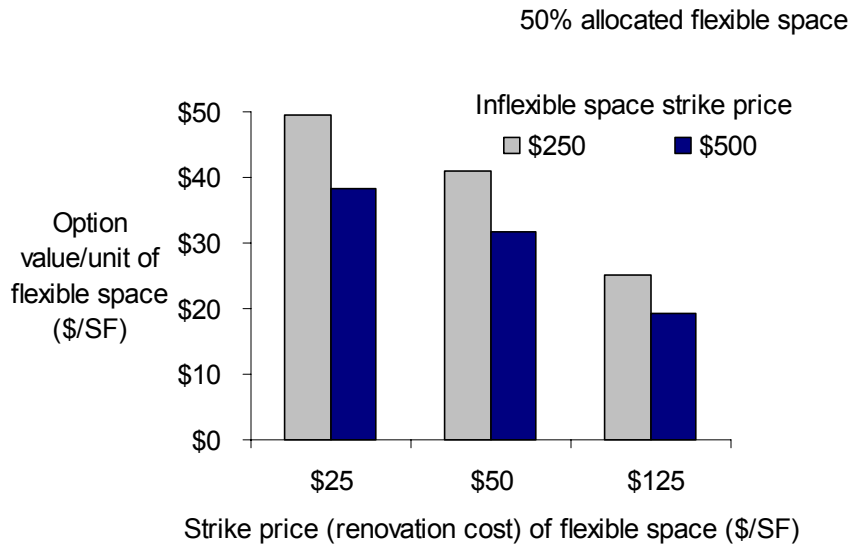


Figure 25. Side-by-side comparison of mean option value results for 50% flexible space for two inflexible renovation cost assumptions.

The ratio of the option value results using the incremental PDF of space need to the option values using the continuous PDF depends on the renovation cost of the inflexible space. With a \$500/SF inflexible renovation cost, the ratio is not a strong function of (flexible) strike price, ranging for example from 115-117 percent for strike prices of \$25-125/SF for 50 percent allocated flexible space. However, for the same scenario but with an inflexible renovation cost of \$250/SF, the range of the ratios is much wider (116-121%). The difference is less pronounced for 100 percent flexible space. For the \$500/SF inflexible renovation cost, the ratio is approximately equal to the ratio of the expected values of the probability distributions (125%). When the inflexible strike price is only \$250, the ratio is slightly lower at 122-123 percent. These results illustrate the importance of performing sensitivity analysis on the inflexible strike price before making generalized conclusions about the dependence of option value on the other variables.

4.4.5. Possibility of reversion

For the model that considers the option to revert to the original space-type (e.g., laboratory) after an office space renovation, the base case model is modified to include the additional variables listed in Table 13, including two uncertain exercise dates, a renovation cost for office space (at t_1) and a renovation cost for reverting to the original space-type (at t_2). The two time horizons are both assumed to be the 8-year time horizons shown in Figure 18, independent of each other. The mean time for the first (office) space need is 4.68 years. The mean duration of time before which the original specialized type of space is needed again is another 4.7 years. Thus, the mean length of a lease is 4.68 years, and the mean total elapsed time before the reversion occurs is 9.36 years. The assumed t_1 renovation costs are the ranges described in Table 13. The t_2 renovation cost is assumed to be \$100/SF, which is based on the corporate case study's desire to consider a reversion back to laboratory space. All other inputs are those listed for the base case model in Table 7. As in the base case model, it is assumed that 100 percent of the space is needed on the exercise dates.

Table 13. Additional Input Parameters for 'Possibility of Reversion' Model

Variable	Options Language	Description	Case Study Value
X_1	Strike price for first time period	Renovation cost relevant for first time period (to office space)	\$25/SF, \$50/SF, and \$125/SF
X_2	Strike price for second time period	Renovation cost relevant for second time period (back to original space)	\$100/SF
t_1	First exercise date	Likelihood of timing of renovation (space need) for first time period	8-year time horizon distribution
t_2	Second exercise date	Likelihood of timing of renovation (space need) for second time period	8-year time horizon distribution, which starts immediately after t_1

The results from the 'laboratory-office-laboratory' formulation of the model are shown in Figure 26. Mean option value varies significantly with the assumed time horizons when the possibility of reversion is considered. Reducing the two time horizons to the 5-year probability distribution reduces mean option value by 70-84 percent compared to the 8-year time horizon results. Increasing the time horizons to the 15-year probability

distribution increases the mean option value by 167-305 percent compared to the 8-year time horizon results. The shorter time horizon provides less time to benefit from greater variation in underlying asset value, and the strike prices are not discounted over as long a time as the base case. Conversely, the longer time horizon provides more time to benefit from greater variation in underlying asset value, and the strike prices are discounted over a longer period of time than the base case.

In this variation of the model, the combined strike price is higher than in the base case model. The price of a lease is comparatively lower, on average, for the 5-year and 8-year time horizons, and it is comparatively higher, on average, for the 15-year time horizon. This is because the length of a lease is defined by the interim period between renovations in the 'possibility of reversion' model, and the mean interim period is the mean of the 5-, 8-, and 15- year time horizons, or 3.5, 4.7, and 10 years respectively. The value of a lease is higher than in the base case model, in which the lease is assumed to last for 5 years for all choices of time horizon. The competing effects on mean option value are seen as a function of time horizon by comparing Figure 19 and Figure 26. For the 5- and 8-year time horizons, the 'possibility of reversion' option value is less than the results from the base case model, which considered only a single renovation. The effect of greater renovation costs and lower (on average) lease price cause the relative decrease in mean option value. However, for the 15-year time horizon, the mean option value is greater than in the base case. The higher lease price in the 15-year horizon(s) case makes the option valuable for higher strike prices, and thus, mean option value is increased.

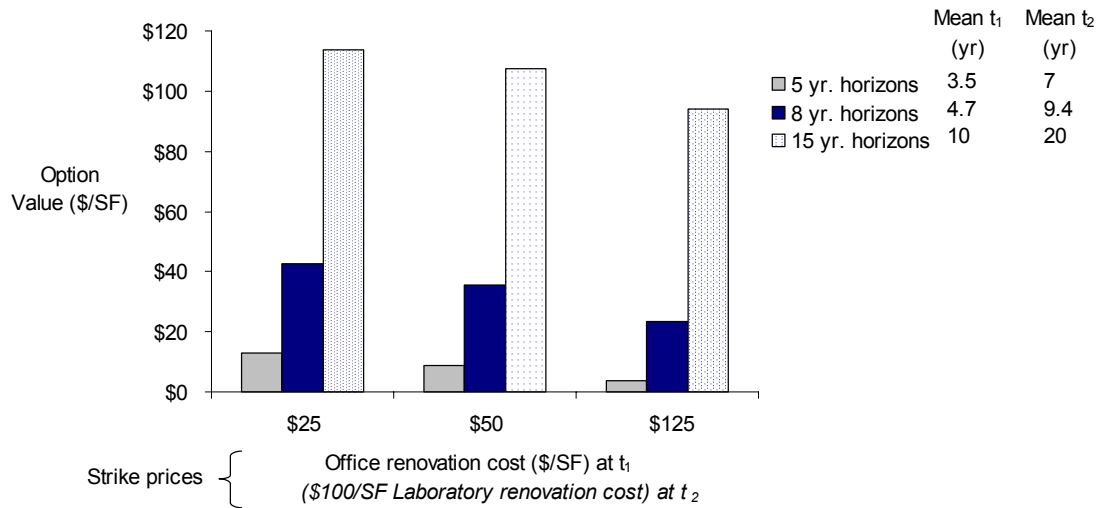


Figure 26. Results for various time horizons for ‘possibility of reversion’ option model formulated to simulate conversion from laboratory to office and back to laboratory. The laboratory renovation cost is \$100/SF.

Sensitivity analysis to laboratory renovation cost (at t_2) is given in Figure 27. Increasing the laboratory renovation cost from \$100/SF to \$150/SF reduces the option value by 20-13 percent (for office renovation costs of \$25-\$125/SF), as expected due to the greater cost of exercising the option. Adding in a factor of 2 percent to represent annual inflation in renovation costs reduces option value by 10-12 percent (for laboratory renovation costs of \$100/SF at time zero).

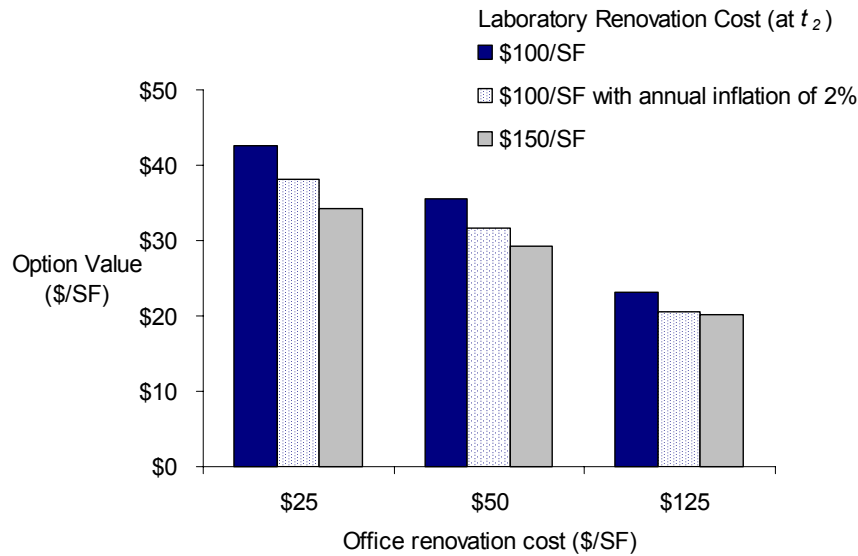


Figure 27. Various renovation cost scenarios for lab-office-lab model (8-year time horizons).

4.4.6. Two-period (compound option value)

The case of adding a second exercise date, as described previously, can be valued as a) a compound option, in which the option can only be exercised in the second time period if it was not exercised in the first period, or as b) an additive option, in which it can be exercised in both periods. The compound option methodology includes the imaginary second period option value in determining whether or not to exercise in the first period, or leave the option open for the second period (Copeland and Antikarov, 2001). The additive model is constructed so that the first period exercise decision does not consider the potential second period option value, and, rather, only considers whether or not renovating offers savings compared to renting, as in the general base case model. Both models use a corresponding truncated (second) event tree. See Appendix C for further description of the two-period model and the relevant equations.

The input parameters introduced in the two time period model are listed in Table 14. The same 8-year probability distributions for the exercise date are assumed to apply to both time periods of the two-period model. The renovation cost of the second time period is set to a slightly higher value than the first period for two reasons. First, renovation costs

are likely to increase in the future, albeit not in a jump manner as indicated by using a single cost for each time period. Second, and most importantly, the first option is almost never exercised in the compound model if the second period strike price is the same as in the first period. The second strike price must be somewhat higher than the first strike price so that it is not always beneficial to leave the second option open. Exact characterization of the relationship between the two strike prices is complicated by the stochastic exercise dates. Values of \$50/SF ($2S_0$) and \$62.50/SF ($2.5S_0$) for X_1 and X_2 respectively result in non-zero first period option values when the length of both time periods is two years (total elapsed time of four years). All other inputs are those listed for the base case model in Table 7. As in the base case model, it is assumed that 100 percent of the space is needed on the exercise dates.

Table 14. Additional input parameters for the Two Time Period compound model and base case values used to obtain results shown in Figure 28.

Variable	Options Language	Description	Case Study Value
X_1	Strike price for first time period	Renovation cost relevant for first time period	\$50/SF ($2 S_0$)
X_2	Strike price for second time period	Renovation cost relevant for second time period	\$62.50/SF ($2.5 S_0$)
T_1	First exercise date	Likelihood of timing of renovation (space need) for first time period	8-year time horizon distribution
T_2	Second exercise date	Likelihood of timing of renovation (space need) for second time period	8-year time horizon distribution, which starts immediately after T_1

The results, shown in Figure 29, provide several insights. First, the two-period *compound* mean option value is \$126/SF for a space that can be renovated for \$50/SF in the first 8-yr time period and \$62.50/SF in the second 8-year time period. This is slightly more than double the single period mean option value calculated in the base case model (i.e., mean option value of \$62/SF for exercise cost of \$50/SF with same 8-year exercise date time horizon and other input parameters). Thus, for a space that can be renovated to office space for the stated costs over the *two* 8-year time periods, it is worth \$126/SF in design and construction fees to achieve such a space. The significant increase in option value with consideration of the second time period illustrates the impact of increased time on option value as it outweighs the value-reducing effect of discounting.

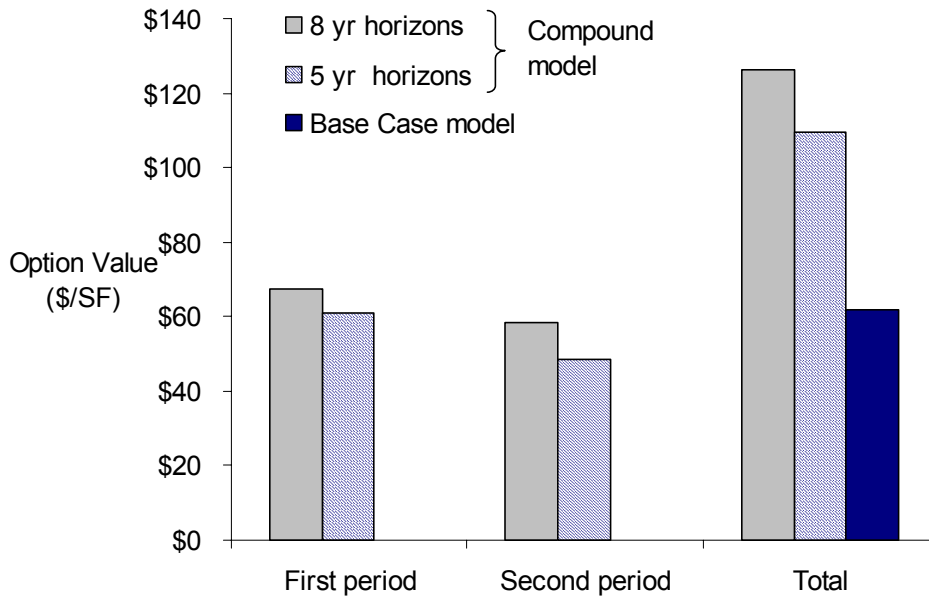


Figure 28. Two-period compound option model for two sets of time horizons and comparison to single period Base Case model result for 8-year time horizon. The strike price is \$50 for the first time period (including Base Case model) and \$62.50 for the second time period.

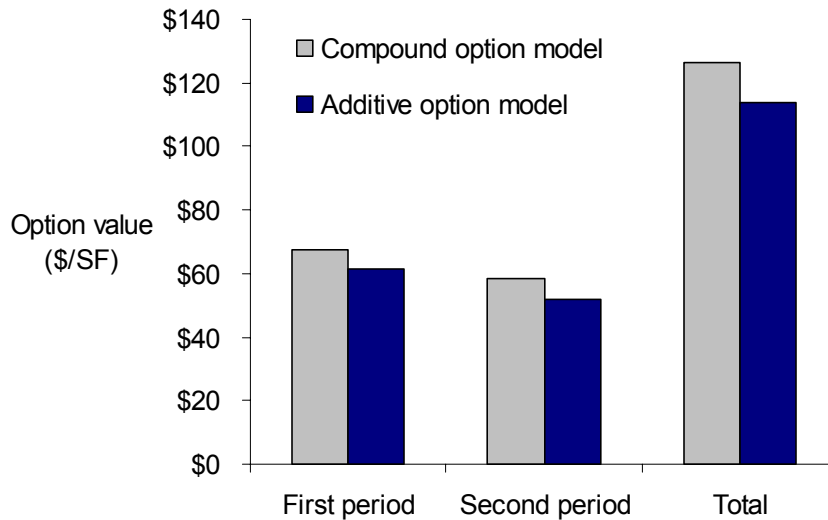


Figure 29. Comparison of the compound option model results to the additive model results, in which the first period decision is independent of the second period value. Input values: 8-yr time horizon PDF for both periods (mean 4.68 yrs); X_1 \$50/SF; X_2 \$62.50/SF ; Each bar represents mean of 10,000 Monte Carlo trials; S_0 \$25/SF/yr, σ 0.1, 5-yr lease at 10% OCC (\$98 current lease), r_f 5%.

The second insight is that, for the given parameters, the compound option value is only slightly higher (10 percent) than the additive two-period model that does not consider the second period when making the first-period decision. This result suggests that decision making based on comparing current rental costs to renovation costs are not greatly in error, value-wise, when compared to a decision that would also take into account the possibility of leaving the option open to renovate in a second period. Furthermore, the result suggests that the first-period decision need not necessarily take into account the value of leaving the option open for the second possible renovation. This result may not be general across other case studies, and thus it is recommended that future studies that wish to consider the value in subsequent ability to renovate use both a compound and additive model to assess the problem.

Sensitivity analysis was performed for the compound model for the variables of time horizon probability distribution and exercise costs. Figure 28 shows the results for 8-year and 5-year time horizons. The mean option value for the 5-year time horizon is less than for the 8-year time horizon (total is 13 percent less), as expected due to the two reasons of less time to reach greater savings from the option and less time over which the value is discounted. Another sensitivity analysis was performed to determine the impact of a 2 percent rate of inflation on the strike prices. The total option value decreased by 7 percent with the inflation factor applied to the strike prices. Reducing the second period strike price to 2.25 times the initial underlying asset value (or \$56.25) increases the first period option value by 2 percent, the second period option value by 5 percent, and the total option value by 3 percent. It is expected that option value increase as strike prices are reduced, and vice versa. Finally, if the strike prices of both periods are set equal (to \$50/SF), the result is obtained that option value is approximately the same for both time periods at \$65.22 and \$65.69 respectively. The total option value is \$131, which is 4 percent greater than the original result. When the strike price is the same for both periods, the option is almost never exercised in the first period, as it is more valuable to leave the option open for exercise in the second period. The first period option value reflects the value of the 'open' option. The two period option values are nearly the same

because they are calculated with nearly the same event trees (since nearly no nodes are truncated for creating the second tree). The slightly higher second period option value reflects the fact that a few non-valuable nodes are truncated and the exercise date value is discounted over a longer time period.

4.5. Discussion on use of results for decision-making

The option value results provide information to decision-makers who are considering investing in the flexibility to change the use of a space. When using the results, it is important that they are aware of the assumptions on time horizon, amount of space needed, renovation costs, and other relevant parameters. Using the real options valuation results, design team can screen architectural designs according to two factors:

1. Estimated cost to renovate the particular design, and
2. Estimated initial cost to achieve that level of flexibility.

For example, as seen in Figure 19, a design that can be renovated for \$25/SF should have up to \$79/SF invested in its design and construction. For that scenario, the recommendation is not highly sensitive to time horizon.

If the team extends the design to consider reversion to the original space for an estimated cost of \$100/SF, the results of Figure 26 are used. The option value from the ‘possibility of reversion model’ is only \$43/SF. This is significantly lower than the base case result of \$79/SF for two reasons. First, the duration of the office space lease is a stochastic variable in the possibility of reversion model, and the mean duration of 4.7 years is less than the five years assumed in the base case. Second, the overall strike price is much higher when the reversion is considered.

If the design team wants to consider only making a fraction of the space flexible, due to uncertainty in how much of the space might actually be renovated (i.e., needed) in the future, the results of the uncertainty in amount of space model are used. The team can choose to designate a certain amount of space as flexible, weighing the benefits of constructing various amounts of flexible space against the initial cost of investment. For example, using the results shown in Figure 22, which assumed a uniform probability

distribution on the amount of space needed with mean of 50 percent, a design in which all of the space can be renovated to office space for an estimated \$25/SF should cost no more than \$40/SF in additional design and construction costs as compared to an inflexible, standard architecture. However, if only 25 percent of the space will be designated as flexible, the allowance for investment in flexibility increases to \$57/SF per unit of flexible space. If the budget for initial investment in flexibility is small, the design-team may consider a design that has a \$50/SF renovation cost, for which no more than \$31/SF should be invested (for 100% flexible space) or \$51/SF (for 25% flexible space). The results from the uncertainty in the amount of space model are significantly lower than the base case, as expected since less future office space is needed on average (i.e., 50 percent on average compared to 100 percent with certainty in the base case).

The base case results may be interpreted as an upper bound on option value for the following two scenarios when the same time horizons and other assumptions are assessed:

- Uncertainty in amount of space – the fraction of space needed on the stochastic exercise date is also stochastic,
- Possibility of reversion – the space may need to be reverted back to its original use at a second stochastic exercise date, and the total cost of converting twice is compared to simply leasing office space for the interim time period and not renovating at all.

These two scenarios, by including other variables, also provide more guidance to the design in the form of how much space should be constructed as flexible space and how costly a renovation should be to revert back to the original use. Clear communication of assumptions used in the real options modeling will help the design process and vice versa.

Decision-makers may also be interested in how much *more* to invest in the design and construction of a flexible space as compared to another, less flexible case. The previous discussion focused on the total value in being able to convert a space to office space for a specified renovation cost. To compare the difference in the value of flexibility between two scenarios with different exercise costs, all other things equal, the option value results

are subtracted. For example, imagine that the \$125/SF renovation cost scenario in Figure 19 characterizes a baseline, inflexible scenario consisting of a basic building shell and structure that, for an additional future investment of \$125/SF, could be turned into office space. Another example of this scenario might be laboratory space for which it is estimated that expending the large sum of \$125/SF in renovation costs would achieve a conversion to office space. The \$31/SF mean option value (for \$125/SF exercise costs) represents the intrinsic value of simply owning a building structure and shell (or laboratory, for example) that gives the owner the right, but not the obligation, to obtain office space by investing the extra \$125/SF in the future. Now imagine that the designers want to create a highly flexible space – one that will only cost \$25/SF in the future to turn into office space. The designers know how much is generally spent on baseline building structure and shell (independent from real options valuation exercises) and they want to know how much extra should be spent on the flexible design as compared to the baseline “shell and structure” scenario. To determine the extra amount, they will calculate the difference between the option values of the flexible (\$25/SF exercise cost) and inflexible (\$125/SF exercise cost) scenarios. Thus, given a baseline shell and structure to work with (e.g., a baseline laboratory), they know that it is worth an extra amount equal to this difference to be able to renovate the space to office space for only \$25/SF in the future, instead of \$125/SF.

The models presented in this chapter are relatively transparent and thus should be accessible to design teams in practice. The basic modeling technique is an improvement on net present value (NPV) and first-cost based decision-making techniques in that it explicitly accounts for uncertainty and the ability of managers to make an economically rational future decision (between renting and renovating). The binomial lattice-simulation model with risk-neutral pricing is applicable to designs that could be converted to *office* space per the market-based assumptions on the underlying asset (i.e., lease price of alternative space). For specialized types of space, such as laboratories, classrooms, cafeterias, and libraries, a well-functioning, liquid market does not likely exist for ‘trading’ these assets. Thus, it is not viable to extend the basic binomial lattice,

risk-neutral pricing model put forth in this chapter to the valuation of specialized space-types as underlying assets.

However, the concept of highest and best use (HBU)⁶ suggests that the option value of the flexibility to renovate only to office-type space represents an approximate minimum on option value if renovations to other space-types are also possible for the same renovation cost. The HBU concept suggests that the space-type with the highest rental value would be chosen on the exercise date. Thus, option value calculated with a single space-type represents a minimum because a) if other space-type values are lower on the exercise date, office space would be chosen, and b) if other space-type values are higher, they would be chosen, thus making the value calculated with the office space value a minimum. Inclusion of the volatility of the value of other space-types would add to the value of the option, not affecting the lower bound characteristic of the office-space calculated option value.

The basic approach to flexibility in building design presented in chapter 3 applies equally to flexibility to convert to other types of space. To evaluate options specifically on other types of space, different types of models, such as simulation, are needed to describe the behavior of the underlying asset and determine the value of the option. Possible sources of information for the value of non-office spaces include internal rents at the organization and the estimated average per unit cost of constructing or adding the new space. Uncertainty in these costs may be considered in a simulation model. The organization may also check its regional real estate market to see if market values are available for the relevant space type. Simulation models would be unique to each organization, and accumulated experience would improve application of the model to each new design project.

⁶ In a well functioning competitive market, no participant on either side of the market (i.e. supply or demand) can be made better off by a change away from equilibrium without making someone else worse off (Geltner and Miller, 2001). This condition is known as Pareto optimality. In the long run, land parcels tend to be used at their HBU because market players are seeking the optimal condition. In more practical terms, the concept of HBU means that if a landlord could get a higher rent, or higher profitability, from another tenant, the current one would be replaced by the higher paying tenant.

Finally, there are a few aspects to consider when merging real options based decision-making into current decision-making structures. First, it may be difficult for facilities managers to justify an expenditure on something that may (or may not) be needed in the future, at which point another expenditure would also be needed. Thus, new review and reward systems for managerial performance are needed under real options based decision-making. Second, it may be useful to place option value results in a life cycle cost framework to determine the total expected present value of the costs (initial investment in flexibility plus the future expenditure of strike price or rent). Furthermore, because the building shell will be used for another productive use before the option might be exercised, it contributes to investment value of the building *before* the exercise date. This value should be worked into overall discounted cash flow analysis of a project. Finally, maintaining records of renovations, as suggested in the “Execute and Monitor” step of the framework, will help validate options based-design and decision-making techniques.

4.6. Chapter conclusion

The real options methodology developed in this chapter is aimed at supporting corporate real estate and developers’ decisions regarding economically rational investments in adaptable spaces. The methodology advances a more strategic view of space design by formally addressing risk and providing a financial result that can be communicated to strategic level members of the organization. The model is an example of a hybrid financial-simulation real options model. A financial model (i.e., the binomial lattice) is used to model uncertainty in the price of office space rent and to value the option. Monte Carlo simulation is used to model uncertainty in parameters such as timing of space need, amount of space needed, and the possibility of reverting to the original space type. Although the theoretical assumptions of the financial type model limit its application to conversion to a space type that exists in a competitive, liquid market (i.e., office space), it is argued based on highest and best use rationale that the result therefore provides a lower bound on option value, if the design allows for conversion to other types of space for the same (or lower) strike price.

The base case model showed that, as with a standard call option on a stock, the option value to renovate increases with a longer time horizon and decreases with increased renovation cost. The sensitivity of option value to time horizon increases with the strike price. The value of the flexibility to renovate is sensitive to the parameters of the lease (i.e., opportunity cost of capital and the duration of the lease), but it is not sensitive to a moderate rate of inflation (i.e., two percent annually) in strike price. It is shown that even inflexibly designed spaces, or ones that cost \$500/SF to renovate to office space, have some inherent option value.

Several insights were produced by modifying the base case model to consider ‘uncertainty in the amount of space needed,’ the ‘possibility of reverting to the original space type,’ and the compound option of a second period in which to renovate. The first variation included a design parameter for the amount of flexible space. It is shown that the total option value increases as the amount of flexible space increases. However, the option value *per unit* of flexible space cannot be monotonically characterized as a function of renovation costs. In the ‘possibility of reverting to the original space type’ model, the value of the flexibility to convert is compared to obtaining a lease for the interim period of time. For the 5- and 8-year time horizons, the ‘possibility of reversion’ option value is less than the results from the base case model, which considered only a single renovation; however the 15-year time horizon assumptions result in higher option value than the base case model. In the two-period compound option value, it is shown that, for the given inputs, the compound option value is only slightly higher (10 percent) than the additive two-period model that does not consider the second period when making the first-period decision. This result suggests that decision making based on comparing current rental costs to renovation costs are not greatly in error, value-wise, when compared to a decision that would also take into account the possibility of leaving the option open to renovate in a second period.

Given the presence of the Black-Scholes formula on most pocket-financial calculators, several approximations are given which may be used to make initial, guiding estimates on option value for flexible space, which is a call option on obtaining the space type. First,

the Black-Scholes formula can be used to determine the upper limit on the value of a design that can be renovated to office space. When timing of the date of space need is uncertain, use of the maximum possible date as the exercise date t in the formula yields the maximum value of a call option to renovate a space to office space. Second, if it is assumed that 100 percent of the space will be needed on the exercise date, the expected value of the exercise date can be used in the Black-Scholes formula to approximate option value, for the probability distributions of exercise date assumed in this study. It is unknown how the Black-Scholes formula would agree with the binomial lattice, simulation model if the probability distribution for the exercise date had a different form. For the variations of the base case model considered, Black-Scholes approximation is possible for a limited set of cases in the ‘uncertainty in amount of space’ model, but it is not representative for the ‘possibility of reversion’ model.

5. Flexibility as an Implementation Strategy: Natural Ventilation

Motivated by the observation that risk aversion hinders adoption of sustainable, innovative building technologies despite recognized potential benefits, this chapter focuses on applying flexible design to one such sustainable building technology: the passive cooling strategy of natural ventilation (NV). In this real options model, the technical performance of a physical system operating within a stochastic environment determines a) the exercise date and b) part of the option value. These two features set this real options exploration apart from other work and may be further applied to the design of technical systems where technical uncertainties, as opposed to market uncertainties, largely impact operating performance and value.

Natural ventilation provides for a building's cooling needs by means of operable windows, stacks and other openings that facilitate air movement driven by thermal buoyancy or wind. A naturally ventilated building that uses stacks to facilitate vertical movement of air is pictured in Figure 30. Before invention of "refrigeration machines for comfort cooling" in the late nineteenth century, buildings were designed to maximize the effect of natural ventilation (Gladstone, 1998). Today, air-conditioning accounts for approximately one-quarter of electricity consumption in U.S. commercial buildings, which equates to eight percent of the country's total electricity consumption (U.S. EIA, 2003). The significant amount of energy used to cool commercial office buildings is a top priority of government funded research and policy (Loftness, 2004).

Natural ventilation is one strategy that can reduce a building's electric (i.e., fossil fueled) cooling needs and, thus, its energy bills (Spindler et al., 2002; Standeven et al., 1999). Furthermore, if a building's cooling and ventilation needs can be met by natural ventilation alone, without the need for mixed-mode or hybrid mechanical and natural cooling, then the capital equipment requirements are less, which may lead to first-cost savings. Additionally, studies show that buildings designed for natural ventilation and hybrid cooling have better indoor environmental quality than their mechanically cooled and ventilated counterparts and thus improved occupant satisfaction and worker

productivity (Wyon, 1996; Sensharma et al., 1998; Standeven et al., 1999; Brager and de Dear, 2000). However, in the era of air-conditioning, or mechanical cooling (MC), the risk that a naturally ventilated building will provide less than constant-comfort conditions inhibits its use (Raue et al., 2002).



Figure 30. Stacks facilitate airflow in this naturally ventilated building at Nottingham University's campus in the United Kingdom. (Photograph by Brian Dean)

To avoid the risk of an overheated building while still maintaining the opportunity to benefit from NV in amiable climates, a NV building could be designed with an option to install mechanical cooling (MC) in the future. The NV building with option (NVO) has two benefits

2. Reduced cooling energy consumption, and
3. Avoidance of, or delay of, the capital cost of chillers, cooling towers, and other equipment.

A simulation model of building thermal performance, including interior comfort conditions, is required to value the real option to install MC in an otherwise naturally ventilated building subject to climate uncertainty. Additionally, although not further assessed in this study, initial feasibility studies need to confirm that the quality of the outdoor air for the building's particular location is good, since the outdoor air will not generally be filtered in a NV design. Furthermore, as with any HVAC system, proper design is needed to insure that good indoor air quality is achieved. Computational fluid

dynamics (CFD) is one simulation tool that designers can use to determine that all volumes of indoor air benefit from fresh outdoor airflow (Tan and Glicksman, 2005).

In the model presented herein, the decision to exercise the option to install MC is based on comfort criteria alone. Thus, although concerns regarding uncertainty or “spikes” in electricity prices motivate consideration of energy efficient building designs, they do not impact the exercise decision for the option to install MC in this study. Treatment of electricity prices is discussed in detail in Section 5.10. A small set of stochastic mathematical equations for option value cannot be devised because the interior temperature of a NV building, which determines exercise, is a non-linear variable that depends on multiple input parameters and preceding time step results. The model for valuing the flexible design presented in this paper is based on stochastic weather generation, building energy simulation, and real options analysis. The results demonstrate how a flexible design strategy that addresses identified risk(s) can hedge losses, provide opportunities, and result in a more economically rational investment.

Current practice for justifying increased first costs⁷ for energy efficient building designs is to compare the life cycle costs (LCC), consisting of equipment and estimated energy costs over a predetermined time frame calculated with expected values of typical climate, to the life cycle costs of a standard building. The difference in the real options methodology as compared to a LCC methodology is twofold. First, the real options model recognizes that there is uncertainty in weather, which is a major determinant of the energy and comfort performance of a building’s cooling strategy. Incorporation of this uncertainty provides a much more complete analysis of the building’s performance, as shown by Jiang and Hong (1993) and Hokoi and Matsumoto (1993). Second, and in contrast to the aforementioned studies, the real options approach protects against the risk of a down-side outcome, such as an overheated NV building, because of the option to install MC equipment at some time in the future. The time frame of the analysis is split into “before” and “after” exercise, corresponding to natural ventilation and hybrid

⁷ It is not necessarily true that more energy efficient buildings have increased first costs, particularly if an integrated, whole building design process is used from the start (Kats et al, 2003).

cooling strategies respectively. These two advantages of a real options approach result in a more thorough understanding, at the design stage, of the future performance of the building and its evolution subject to uncertain climate.

5.1. Identify uncertainties

The major uncertainties affecting the success of a NV building, as illustrated in Figure 31, can be divided into two categories: uncertainties that result in the technical risk of overheating, and uncertainties that result in the market risk of reduced selling/rental value of the building. The technical uncertainties include climate variability and anthropogenic induced climate change; operational difficulty, failure of mechanical components, and/or insufficient control systems; and changes in building use or function that result in changes in the building's cooling loads. Downside outcomes of each of these uncertainties will result in an overheated, or "failed", NV building. The market uncertainty of building value refers to the building's selling or rental value as a function of the NV characteristic as compared to an otherwise equivalent building with MC. Each of these uncertainties and resulting risks are discussed further in this section, and this chapter focuses on a model to value the option to install MC in the face of climate uncertainty (only).

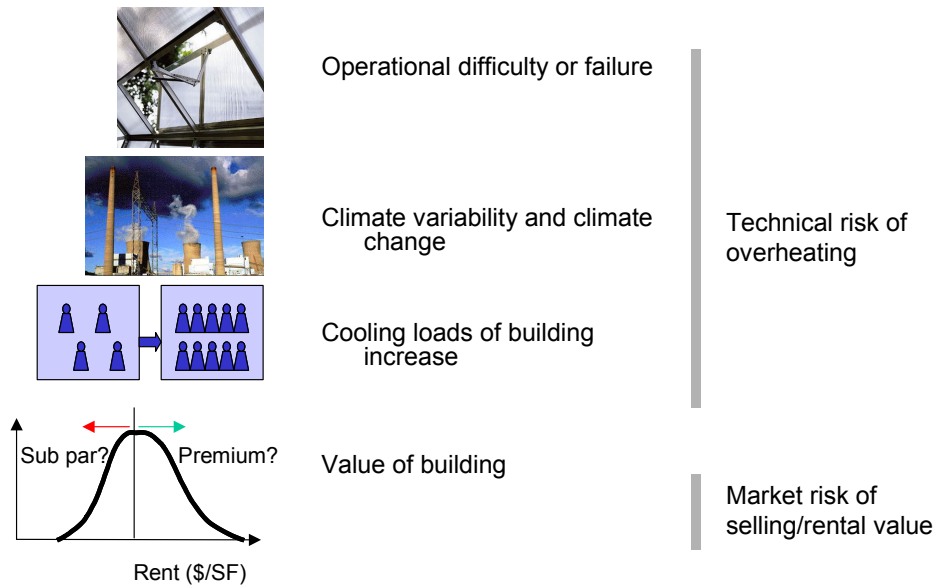


Figure 31. Uncertainties that impact the success of a NV building

Like other passive building design strategies, the performance of a naturally ventilated building depends (partially) on the outdoor climate. Future climate is uncertain, and the (perceived) risks it introduces are exacerbated by the onset of global climate change. Climate uncertainties are especially important in assessing the potential of NV to cool a particular building. The ambient climate partially determines the internal cooling loads and directly determines the exterior air’s cooling capacity (i.e., enthalpy). The primary climate variables of interest to building energy studies are dry bulb temperature, direct normal solar radiation, diffuse horizontal solar radiation, and relative humidity. Typically, assessments of building energy consumption are made using a typical mean year weather data set (TMY2)⁸, thus producing an expected value of energy consumption.

⁸ A TMY2 is a data set of hourly values of solar radiation and meteorological elements for a 1-year period. It consists of months selected from individual years from the period 1961-1990 strung together to form a complete year. A TMY2 data set is distinct from a TMY data set in that it is based on more recent data, including better measurements and/or approximations of solar radiation. The intended use of TMY2 data is for computer simulations of solar energy conversion systems and building systems. The “typical” months are selected using an empirical approach that examines individual months from all years in the period of record. For example, for the period 1961-1990, all 30 Januarys are examined, and the one judged most typical is selected to be included in the TMY2 data set. The 12 selected typical months for each station were chosen from statistics determined by using five elements: global horizontal radiation, direct normal radiation, dry bulb temperature, dew point temperature, and wind speed. These elements are considered the

If, instead, extreme “design day” weather assumptions are used, NV may be disqualified as a cooling strategy even if it is adequate for a majority of the time. Therefore, to properly evaluate the performance of a NV building, simulated stochastic climate is needed as input.

Some of the technical risks identified with NV include (Raue et. al., 2002):

- Localized high temperatures
- All-around high temperatures
- Insufficient ventilation rates
- Drafts
- Variability in occupant control
- Sensation of dry air, and
- Noise transmission through ventilation grills.

A comparison of the list of risks for natural ventilation with a list of typical complaints regarding comfort levels in air-conditioned spaces shows that these problems are not unique to natural ventilation. However, thermal environments found in NV buildings are typically more variable and less predictable than those found in air-conditioned buildings, but not necessarily less comfortable. In research conducted to refute the standardized ventilation and thermal comfort standards for office buildings in the U.S., Brager and de Dear (2000) found that workers in NV buildings are satisfied with a wider range of indoor climatic conditions. They also found a strong correlation between having access to operable windows and satisfaction with air movement, ventilation, and air quality.

Another uncertainty of concern for NV is the building’s future market value, or level of rent that it can command. The technical uncertainties of NV performance have a direct impact on the market value of a building. Commercial office buildings in the U.S. are divided into different classes to distinguish their physical and locational qualities, and therefore the levels of rent that the demand side of the market will pay (Geltner and Miller, 2001). Physical qualities assessed include energy costs and comfort conditions;

most important for simulation of solar energy conversion systems and building systems. Because of the selection criteria, TMY2s are not appropriate for simulations of wind energy conversion systems. Source:

thus MC is standard in the highest classifications (i.e., class A). However, recent research, motivated by the need to reduce building energy consumption, has brought much greater technical sophistication to the design and control of naturally ventilated buildings. Thus, NV is an innovative technology that could be used in place of MC in acceptable climates, such as the UK, Netherlands, and temperate climates in the U.S. (Spindler et al., 2002).

5.1.1. Hybrid cooling strategy

In many cases, NV is best considered as part of a hybrid cooling (HC) strategy – one that combines mechanical heating, ventilation and air-conditioning (HVAC) systems with NV. Hybrid cooled buildings provide inherent flexibility and redundancy in the space conditioning systems of a building, resulting in potentially longer life and greater adaptability to changing uses. A hybrid system also includes the relative advantages of a mechanical system, such as reliability of performance and ability to filter air when needed. Strategies to consider to obtain the best performance from a HC building include the following (Dean, 2001):

- Employ mechanical ventilation before mechanical air-conditioning, using properly positioned fans, which consume approximately one-tenth as much electrical energy as air-conditioning systems.
- Cool the building at night, using thermal mass such as concrete or granite.
- Dehumidify the air using desiccant dehumidification, as air often feels better at lower relative humidity, even at a higher temperature.

In this research, the concept of a hybrid cooling and ventilation strategy is decomposed into two stages.

5.2. Define flexibility

To address the risk of overheating, the flexible building’s cooling strategy consists of NV together with the *option* to install MC in the future. Initial screening models are used to verify that the “base” building design and local climate are suitable for NV alone to provide cooling. As illustrated in Figure 32, the possibility of never needing mechanical

cooling equipment, or at least delaying the expenditure, may provide significant cost savings. Using a flexible decision evaluation approach and randomized realizations of uncertain parameters, value can be assigned to such flexibility in a system. The real options model developed in this research evaluates the value of a flexible, two-stage hybrid system, including the operational flexibility in a hybrid-cooled building subject to climate uncertainty.

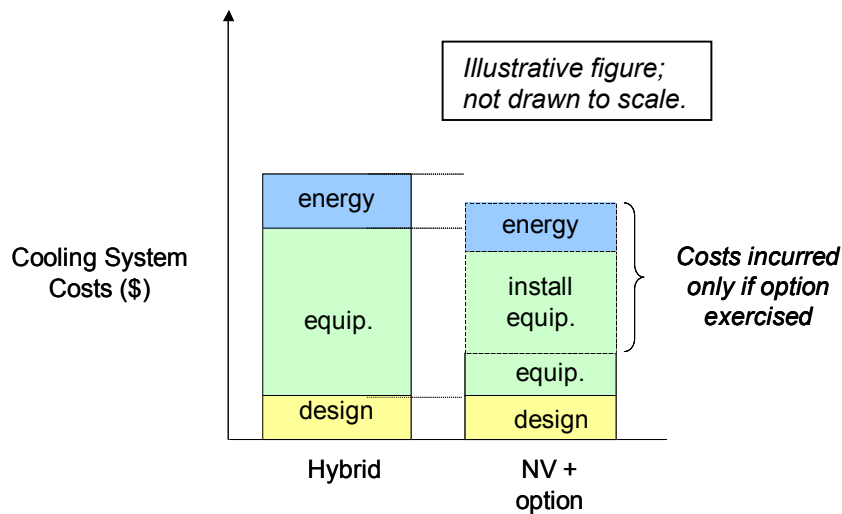


Figure 32. By delaying, and potentially never requiring, the costs of mechanical cooling equipment, the option-based NV building may cost less than a hybrid building.

5.2.1. Conceptual design typology

Figure 33 shows a conceptual design typology for a naturally ventilated building with embedded option to install a MC system. To facilitate future installation of MC equipment, the initial NVO design will likely include the following components:

- Ducts & diffusers
- Cooling coil
- Water pipes
- Space for chiller, cooling tower, pumps, and fans

Additionally, temperature and air quality sensors may be included. Then, if exercise occurs, the MC equipment will be installed, including a chiller, cooling tower, pumps, and fans, as shown in Figure 34. Installation will also require connection of the equipment to the overall control system for the now hybrid-cooled building.

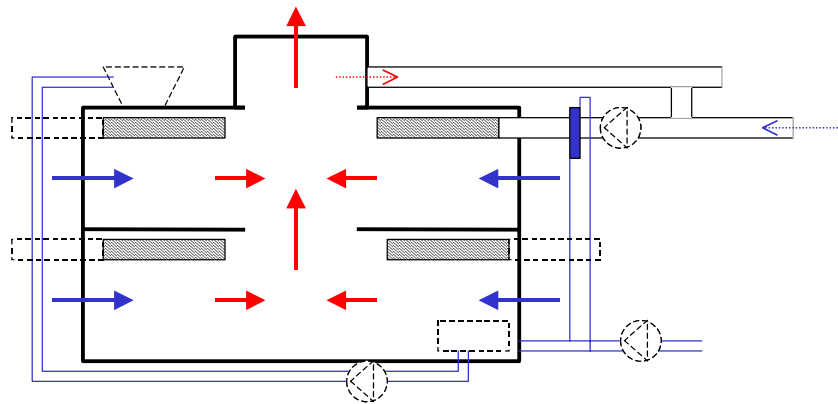


Figure 33. Conceptual design typology for a naturally ventilated building with embedded option to install a MC system.

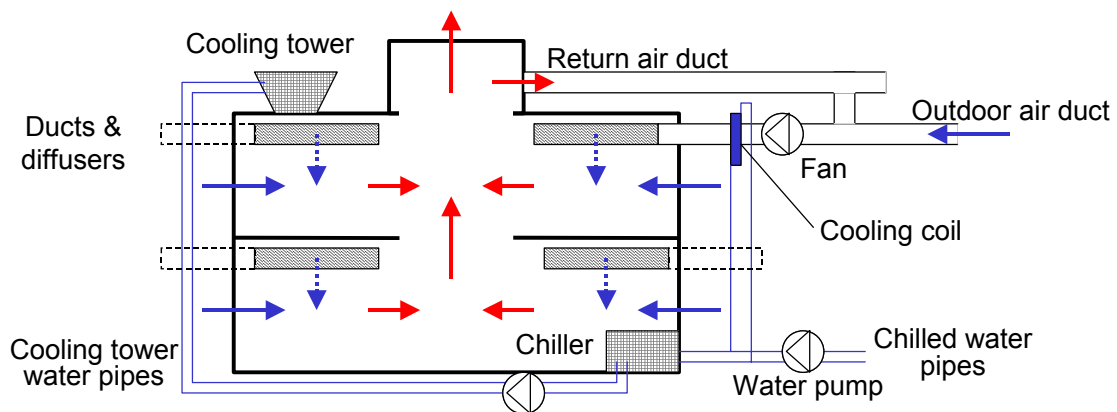


Figure 34. NVO building after exercise is a hybrid cooled (MC and NV) building.

5.2.2. Taxonomy

The option and related terminology are defined as follows:

Option: The option is defined as the ability to install mechanical cooling in an otherwise naturally ventilated building.

Exercise date: The date of exercise is determined by the comfort conditions within the naturally ventilated building. If the interior temperature is greater than a predetermined maximum for a specified number of hours, the option will be exercised.

Exercise price: The cost to install the mechanical cooling system and other features to create a hybrid (natural-mechanical) cooled building.

Option value: The incremental amount to spend on the initial design and construction of the cooling system of the naturally ventilated building with option. This amount is determined by comparing the option-based building to the costs of a baseline, inflexible mechanically cooled building.

Uncertainty: Climate (ambient temperature) uncertainty is evaluated in this model, and value in the flexible strategy is derived from this parameter. The building can benefit from NV as long as the climate provides acceptable conditions. If the climate becomes too warm, the risk of overheating is hedged by being able to install mechanical cooling.

5.2.3. Components of option value

Figure 35 illustrates the two-phased approach to cooling that the option provides over the lifetime of the building (or the defined analysis period for modeling purposes). During the first phase, the building is in NV mode. The building continues in NV mode as long as the indoor temperature meets comfort requirements. The building may never switch to hybrid mode; thus, the building owners will not have to incur the capital equipment cost of installing the MC system. However, if the comfort criteria are exceeded, the option will be exercised and the building switches to hybrid mode by installing the necessary

features to obtain mechanical cooling. When in hybrid mode, the benefits of the operational flexibility to use MC only when necessary are defined as the energy savings as compared to the otherwise equivalent MC building.

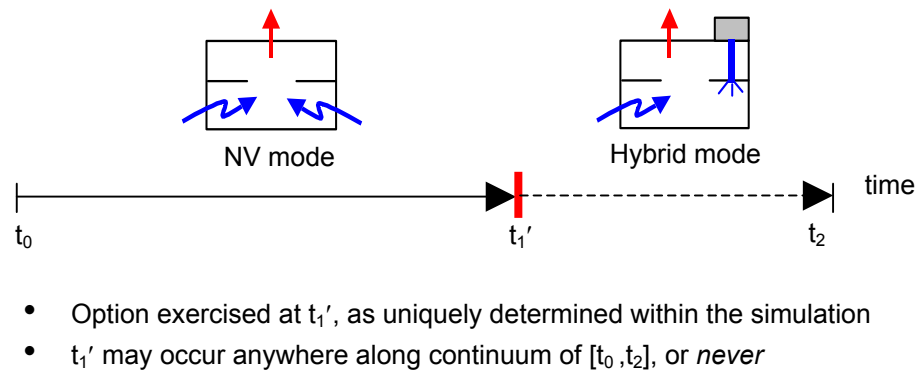


Figure 35. Timeline illustration of the modes in which the option-based NV building can exist.

Provides an illustration of the cash flows for the cooling system of a MC building, consisting of design, equipment, and cooling energy costs. Shows the cash flow illustration for the NVO building. No equipment costs are incurred at the initial time period. Equipment and energy costs are only, potentially, incurred if exercise occurs. Shows comparison of the PV of costs of the MC system relative to NVO. Option value of the flexible NVO cooling strategy is composed of the potential to a) delay or avoid capital costs and to b) consume less cooling energy than the MC building.

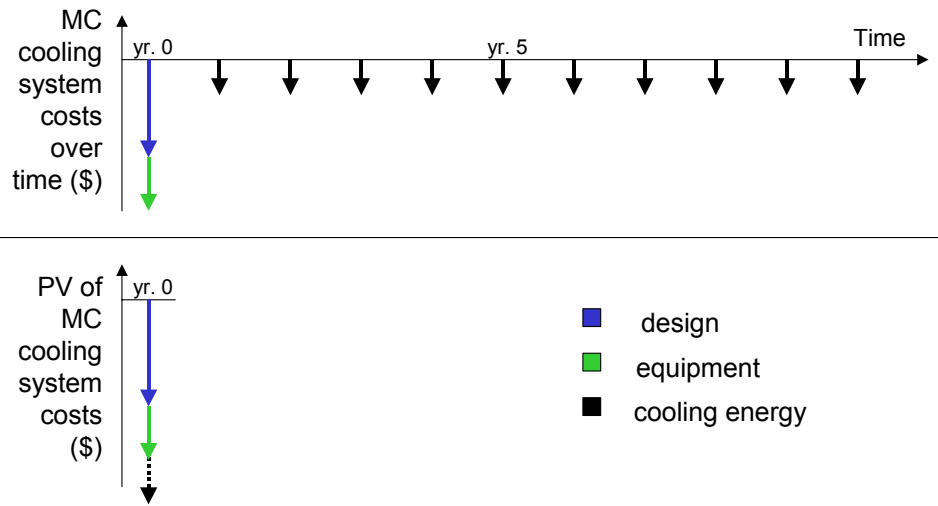


Figure 36. Cashflow and present value illustration of MC building.

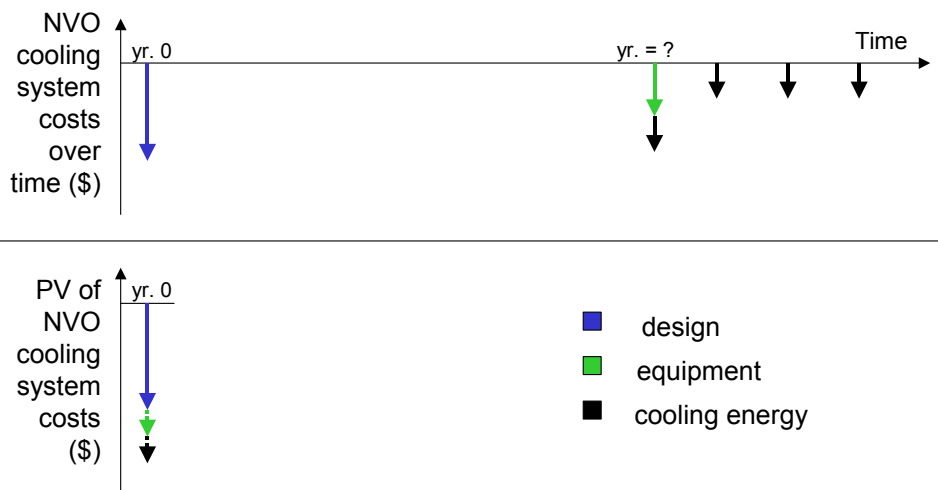
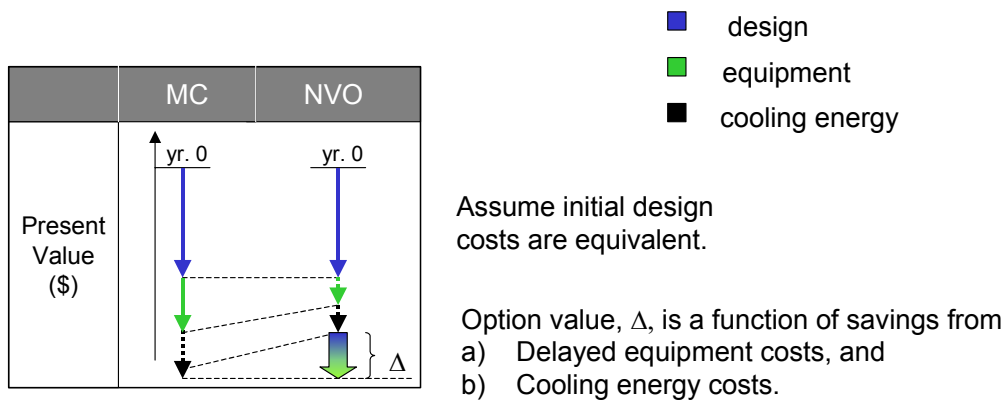


Figure 37. Cashflow and present value illustration of NVO building.



- Thus, if extra must be spent on initial NVO design (and equipment) to obtain the flexibility to install MC in the future, it should be $\leq \Delta$.

Figure 38. Option value is defined by subtracting NVO exercise (equipment) and operating (energy) costs, if they occur, from the applicable equipment and energy costs of the baseline MC building.

5.3. Development of simulation type ROs model (equations)

Building investors and designers would like to know the value of the option-based naturally ventilated (NVO) building, or how much should initially be spent on design and equipment to obtain the option. Option value is defined as the *incremental* benefit of a flexible, naturally ventilated cooling system versus a baseline mechanical cooling system. Defined in this way, option value represents the incremental amount to spend on the initial design and equipment for a flexible natural ventilation cooling strategy relative to the initial costs of a mechanical cooling system. An MC building is used as the baseline rather than a NV building (without option) for two reasons. First, industry is more familiar with MC costs than NV costs. Second, calculation of the energy savings benefit requires use of the more energy intensive system as the baseline. The economic value of the option to install MC in the future is defined by two components, both referenced to a baseline MC building:

1. the capital cost savings enjoyed by the delay or avoidance of cooling system equipment (e.g., chiller), plus

2. the present value of cooling energy cost savings of the NVO building.

The sum of these two components is the incremental option value Δ , which, when added to the initial (design and equipment) costs of a baseline MC building's cooling system, yields information on the total amount to be spent on design, equipment, and flexibility for the NVO cooling strategy.

Development of the model for determining option value Δ begins by defining that the present value of the total costs of the NVO building's cooling system C_{NVO} must be less than or equal to the present value of the total costs of the MC building's cooling system C_{MC} :

$$PV[C_{NVO}] \leq PV[C_{MC}] \quad (5.1)$$

where $PV[\bullet]$ represents calculation of the present value of a stream of future costs. At this early stage, it is useful to note that the modelling results may show that the option is not valuable, in which case, designers should consider improving the building design, using a HC strategy, or using other energy efficient HVAC systems. This will be discussed with reference to numerical results.

The cooling system costs C are generalized into categories of design D , equipment E , and operational (cooling energy) costs O . The present value of the cooling system costs for the MC building are defined as

$$PV[C_{MC}] = D_{MC,o} + E_{MC,o} + PV[O_{MC,t \rightarrow t_2}] \quad (5.2)$$

and the present value of the cooling system costs for the NVO scenario are defined as

$$PV[C_{NVO}] = D_{NVO,o} + E_{NVO,o} + PV[E_{NVO,t}] + PV[O_{NVO,t' \rightarrow t_2}] \quad (5.3)$$

where $D_{NVO,o}$ and $E_{NVO,o}$ include consideration of flexibility so as to be able to install mechanical cooling for a cost of $E_{NVO,t'}$ in the future. Thus, in the NVO scenario, some

equipment costs are occurred at the present time – those needed to obtain the natural ventilation system with option – and some are delayed until the (uncertain) exercise date, or may never be needed. The exercise date costs $PV[E_{NVO, t'}]$ represent the fraction of the MC building's equipment costs that can be delayed in the NVO scenario. If the option is exercised, the NVO building operates in hybrid mode until the end of the analysis period and will incur operating costs $PV[O_{NVO, t' \rightarrow t2}]$ over that second time period.

Operating costs are determined from the building's hourly cooling load $Q(t)$, the coefficient of performance of chiller equipment (COP), and the price of electricity P_{elec} :

$$O(t) = Q(t)COP^{-1}P_{elec} \quad (5.4)$$

Operating, or cooling energy costs, only include chiller electricity costs. Fan energy and other maintenance costs are not included in the model, as will be discussed in section 5.4.2. The present value of the cumulative operating costs for cooling is determined from the hourly operating (cooling energy) costs $O(t)$ and a risk-adjusted discount rate r :

$$PV[O] = \sum_t O(t)(1+r)^{-t} \quad (5.5)$$

Exercise costs $E_{NVO, t'}$, or the costs of cooling equipment installed on the exercise date in the NVO scenario, are assumed to be equal to the fraction χ of MC cooling equipment costs that can be delayed:

$$E_{NVO, t'} \equiv \chi E_{MC, o} \quad (5.6)$$

It is assumed that the estimated exercise costs will increase by the rate of inflation r_i until, and only if, exercise occurs at time t' . The rate of inflation variable may be augmented to represent an additional cost penalty in waiting to undertake installation activities.⁹ The

⁹ For example, because chiller equipment price depends partially on the price of steel, which has a high volatility, sometimes contracts are created to lock-in prices for future delivery of equipment at current

inflated time t' exercise cost is then discounted to the present using a risk-adjusted discount rate r :

$$PV[E_{NVO,t}] = \chi E_{MC,o} (1+r_i)^{t'} (1+r)^{-t'} \quad (5.7)$$

It is assumed that rate of inflation is less than the discount rate. If the option is never needed, the treatment of delayed costs can be bounded by assuming that a) they are automatically incurred at the end of final year t_2 , or b) they are completely avoided. The base case analysis assumes the latter – that the full value of exercise costs represents the benefit of “no exercise” results.

As shown in Figure 39, the MC building’s costs are used as the baseline for determining the option value Δ of the NVO strategy. Option value is calculated by subtracting the delayed, probabilistic NVO building’s cooling system capital costs (i.e., exercise costs) and cooling energy costs from the baseline MC building’s capital and cooling energy costs

$$\Delta = \chi E_{MC,o} - PV[E_{NVO,t}] + PV[O_{MC,t \rightarrow t_2}] - PV[O_{NVO,t' \rightarrow t_2}] \quad (5.8)$$

where $PV[E_{NVO,t}]$ and $PV[O_{NVO,t' \rightarrow t_2}]$ are only incurred if the option is exercised; they are equal to zero if exercise does not occur. It is the probabilistic nature of the NVO costs that gives the option value.

prices to protect against the possibility of price increases (Source. Huang J. Conversation with. March 17, 2005).

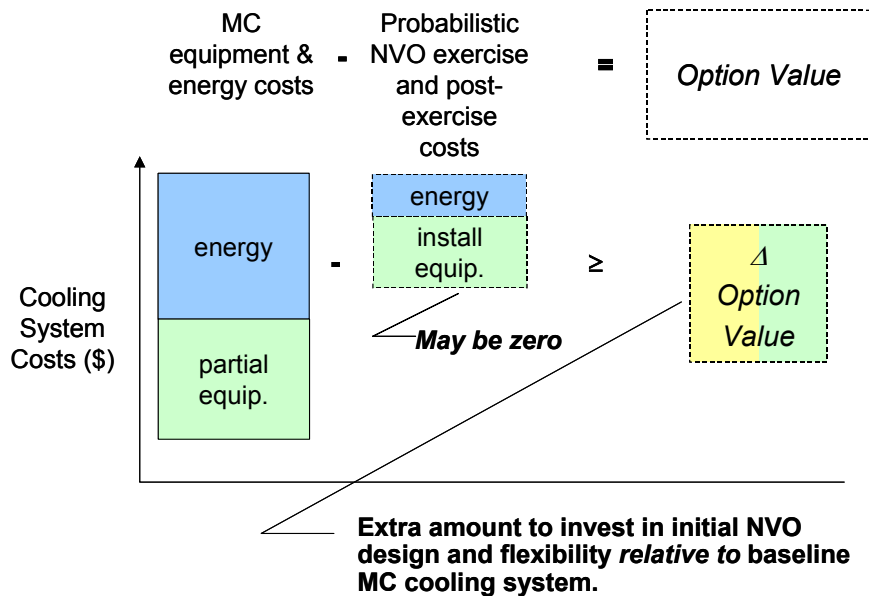


Figure 39. Option value is defined by subtracting NVO exercise and operating (energy) costs from the applicable equipment and energy costs of the baseline MC building.

The model presented herein uses stochastic evolutions of climate to determine the exercise date t' , the MC operating (cooling energy) costs $PV[O_{MC,t \rightarrow t_2}]$, and the NVO (hybrid) operating costs $PV[O_{NVO,t \rightarrow t_2}]$. Multiple runs of the model produce probabilistic information on the difference in operating costs of the two scenarios. The exercise costs, or amount of capital expenditure that can be delayed, depend on the level of flexibility that was initially built into the NVO building. Thus, results are tabulated for a range of exercise costs. Final results represent the maximum incremental amount Δ to spend on initial design and equipment costs of the NVO building's flexible, NV cooling system relative to the first costs (design and equipment) of a MC building's cooling energy system.

As discussed in the first paragraph of this section, decision-makers are also interested in the total amount to spend on the flexible, naturally ventilated cooling system of a NVO

building. An estimate of the maximum first-costs for the NVO scenario, relative to the MC baseline, is found by combining Eq.'s 5.1, 5.2, 5.3, and 5.6:

$$D_{NVO,o} + E_{NVO,o} \leq \Delta + D_{MC,o} + (1-\chi) E_{MC,o} \quad (5.9)$$

Although results for this total will not be presented herein, future applications of the model to specific building case studies can make use of Eq. 5.9. The results herein focus on option value Δ as it represents the benefits of flexibility and natural ventilation, which are the objectives of this thesis.

5.3.1. Generalized calculation of option value

The option value contribution of delayed or avoided capital costs is linear in exercise costs per the calculation methodology specified by Eq.'s 5.7 and 5.8. A generalized result is obtained such that the mean option value for any choice of exercise cost can be calculated. Derivation begins by referring back to Eq.'s 5.7 and 5.8

$$PV[E_{NVO,t}] = \chi E_{MC,o} (1+r_i)^{t'} (1+r)^{-t'} \quad (5.7)$$

$$\Delta = \chi E_{MC,o} - PV[E_{NVO,t}] + PV[O_{MC,t \rightarrow t2}] - PV[O_{NVO,t' \rightarrow t2}] \quad (5.8)$$

The first two terms on the right-hand side of Eq. 5.8 represent the option value due to delayed/avoided equipment costs Δ_E and the second two terms represent the option value due to cooling energy cost savings Δ_O :

$$\Delta_E = \chi E_{MC,o} - PV[E_{NVO,t}] \quad (5.10)$$

and

$$\Delta_O = PV[O_{MC,t \rightarrow t2}] - PV[O_{NVO,t' \rightarrow t2}] \quad (5.11)$$

Substituting Eq. 5.7 for the second term of Eq. 5.11, gives the following the formula for the delayed/avoided equipment costs portion of option value Δ_E

$$\Delta_E = \chi E_{MC,o} - PV[E_{NVO,t}] = \chi E_{MC,o} (1 - (1+r_i)^{t'} (1+r)^{-t'}) \quad (5.12)$$

Let α be equal to the quantity

$$\alpha = (1 - (1+r_i)^{t'} (1+r)^{-t'}) \quad (5.13)$$

Such that

$$\Delta_E = \alpha \chi E_{MC,o} \quad (5.14)$$

The mean value of the factor α can be calculated for a set of simulation trials (using the results for t') and then used to calculate the delayed/avoided equipment costs portion of option value using Eq. 5.14. The factor α is unique to each set of simulations because it depends on the time at which exercise costs must be paid. The mean values for α and Δ_O for all simulations performed are given in Appendix H along with a sample calculation for determining option value Δ using the results for α and Δ_O .

5.4. NVOV model description

The real-options simulation model developed herein will be referred to as the Natural Ventilation Option Valuator (NVOV). The model was created in Java, partly by adapting an existing, rapid calculating building simulation program called the Design Advisor¹⁰. The model uses Excel spreadsheets as user interface and to provide data output. Gabriel Lopez-Betanzos, Course 6 '05, programmed the model, including the interface of Excel with Java, modification of the Design Advisor's one-year simulation capabilities to expand to multiple years, and implementation of the stochastic weather (temperature)

¹⁰ An on-line building energy simulation tool for architects and engineers available at <http://designadvisor.mit.edu/design/>. A technical description of the thermal model is described in a later section.

equations. The model determines the exercise date; the present value of MC operating costs and energy consumption; and the present value of NVO operating costs and energy consumption. The model consists conceptually of three modules, as depicted in Figure 40:

- a stochastic weather model,
- a building (energy) simulation model, and
- a real options decision rule moderator.

The stochastic weather model provides random realizations of outdoor temperature so as to model a stochastic future climate. It also includes a parameter to model the average annual increase in regional temperature due to anthropogenic induced climate change.

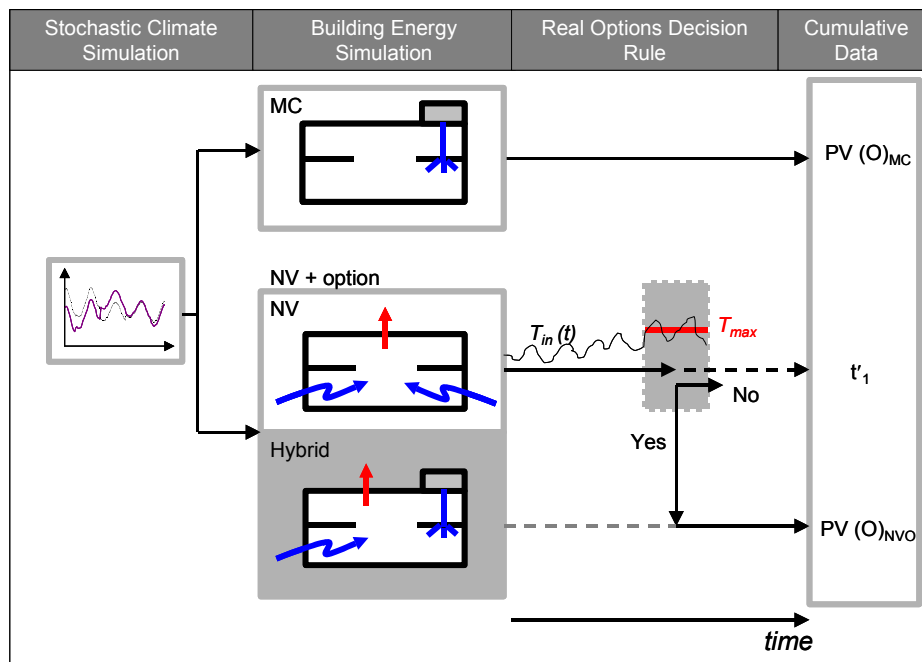


Figure 40. NVOV – a real options simulation model for the option to install mechanical cooling in a naturally ventilated building subject to stochastic climate conditions.

The energy simulation module consists of two buildings analyzed in parallel: one with MC (only) and one with NV that turns into a hybrid cooled building if exercise occurs (i.e., the NVO building). The real options block of the model is the exercise rule moderator, and it oversees each run of the model. It analyzes the simulated comfort of

the NV building to determine if comfort rules are violated. If the comfort rules are violated, the option to install mechanical cooling is exercised, and the simulation continues in hybrid mode until the end of the defined time period of analysis. The timing (t') of exercise is recorded. In addition, the cumulative cooling energy consumed and cooling energy costs of the MC and phase-two NVO buildings are recorded. The model is run multiple times, resulting in frequency distributions of these results.

5.4.1. Stochastic weather generator with climate change

Option value rests on the postulate that uncertainty is resolved over time. Thus, the time dependent component of uncertain variables is of fundamental importance. For this reason, time series of stochastic weather evolution are needed, converse to typical building energy simulations that use a single year of typical TMY2 meteorological data, determined statistically from observed weather data. Multiple sample paths of weather evolution are needed to model the uncertainty in the timing of exercise (i.e., hot periods that results in uncomfortable interior conditions under natural ventilation). The stochastically generated weather time-series are the stochastic inputs for the building energy simulation. The building energy simulator is run once for each weather time-series, consisting of hourly values for temperature, solar radiation, and solar illuminance.

A variety of stochastic weather generating options were explored, as described in Appendix D. Due to the objectives of rapid computing time, integration into the Java programming language, and minimum input assumptions, it was determined that a simplified Gaussian noise method applied to dry-bulb temperature only would be satisfactory for evaluating the option in this research. More complex stochastic weather generators based on statistical descriptions of observed data are described in Appendix D. The Gaussian noise method, as will be described, could also be applied to the solar radiation and illuminance variables. This rapidly computing stochastic weather model will be useful for developing a broad range of models that assess the value of flexibility for climate dependent systems, including renewable energy systems and other cooling systems for buildings.

The simplistic model for generating stochastic dry-bulb temperature is based on applying Gaussian noise (ϕ) and a trend rate (a) to a typical mean year (TMY2) weather data set as follows:

$$T(t)_{new} = T(t)_{TMY} + at + \phi' \quad (5.15)$$

where a stochastically produced hourly data point $T(t)_{new}$ is based on the corresponding hourly data point from the TMY2 data set $T(t)_{TMY}$.

The data source for the trend parameter (a) is MIT's Integrated Global System Model (IGSM)¹¹ (Webster et al., 2003). The IGSM model simulates the mean yearly temperature for the earth's latitude bands under different emissions scenarios. Figure 41 shows the zonal mean, yearly temperature for the 35° latitude band (San Francisco) for the 10-year period 2005-2015 under an assumption that "no policy" is instituted over global greenhouse gas emissions (Webster et al., 2003). Each data point is the average of 250 runs of the model where each run was performed with a different ensemble of (uncertain, probabilistic) input parameters chosen by a Latin hypercube sampling technique. The mean temperature increased by approximately one-quarter of a degree Celsius over this ten-year period.

¹¹ Christ Forest, PhD, Research Scientist with MIT's Joint Program on Climate Change, assisted by providing the raw data from the Integrated Global Climate Model.

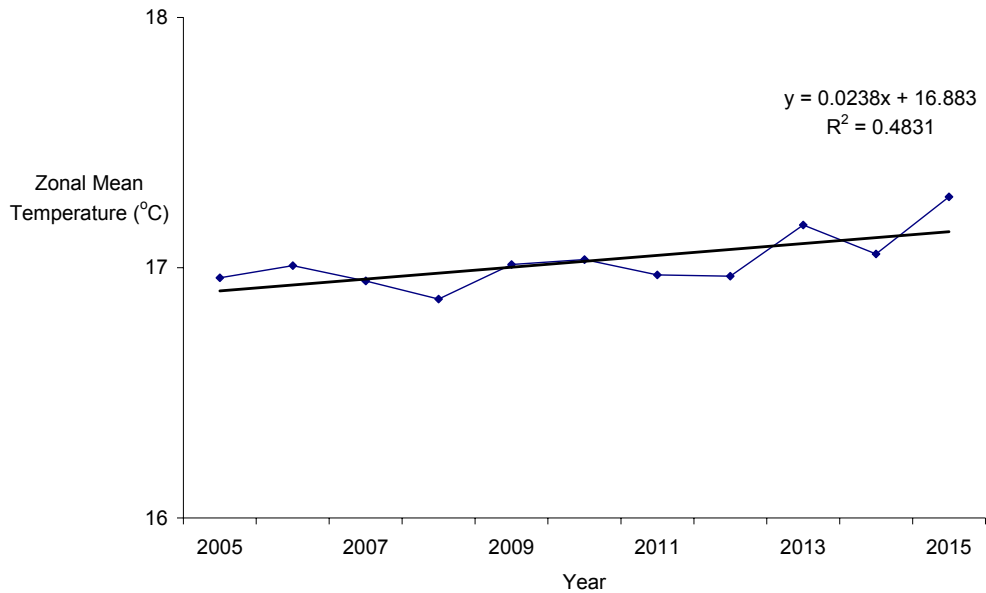


Figure 41. Zonal mean, yearly temperature for the 35° latitude band (San Francisco) calculated from output from 250 runs of MIT’s Integrated Global System Model under “no policy” assumptions.

Table 15 gives results for latitudes applicable to the locations chosen for this study. The first observation is that the integrated climate system model suggests a low rate of mean temperature increase for the latitude bands of 35°, 43°, and 51° over the time period 2005-2015. The second observation is that, in many cases, the temperature increase is higher under “no policy” assumptions than under “policy” assumptions, in which caps are placed on emissions. A third observation is that the rate of temperature change differs between the two time periods analyzed (2005-2015 and 2005-2020) in Table 15. A fourth observation, from Figure 41 and applicable to similar graphs for the other latitudes, shows that the goodness of fit of a linear trend line is poor (R-squared value of 0.48 in Figure 41). All together, these observations indicate that the trend in mean annual temperature increase determined for an entire latitude band, as in the IGSM, is very small for the time period 2005-2015. To improve the data input for the needs of building-energy studies, regional climate model output is needed (e.g., Levermore et al., 2004). Nonetheless, the data presented in Table 15 for the ten-year period 2005-2015 is used as

input for the NVOV model. Because the IGSM-produced values for a are so small, a case will also be tested using a high numerical value for the assumed annual mean rate of temperature increase to test the “what-if” scenario of a high local temperature increase.

Table 15. IGSM results for a (annual increase in regional mean temperature)

Mean annual temperature trend a ($^{\circ}\text{C}/\text{yr}$)				
Latitude band	2005-2015		2005-2020	
	no policy	policy	no policy	policy
35 (SFO)	0.024	0.023	0.011	0.012
43 (CHI, MSP)	0.023	0.023	0.018	0.018
51 (SEA)	0.004	0.004	0.017	0.017

The noise parameter (ϕ) is randomly chosen from a normal distribution with mean zero and standard deviation σ . To keep the model simple, a single value of ϕ' is drawn for each day and then applied to each of the 24 TMY2 temperature data points for that day. The standard deviation of daily temperature (σ) is a user-input parameter for the model. To keep the model simple, a single value applies to the entire year or multiple years of generated weather. Estimates of σ are available from Vinnikov et al. (2002) for Seattle and Chicago. The range of the mean standard deviation of temperature for 1951-1999 is 3-7 $^{\circ}\text{C}$ for Chicago and 2-4 $^{\circ}\text{C}$ for Seattle. Published estimates of standard deviation in daily temperature are not available for San Francisco or Minneapolis, so similar choices to the other two cities will be used. Several stochastically generated sample paths of hourly temperatures for summer months in Chicago two years hence are shown in Figure 42.

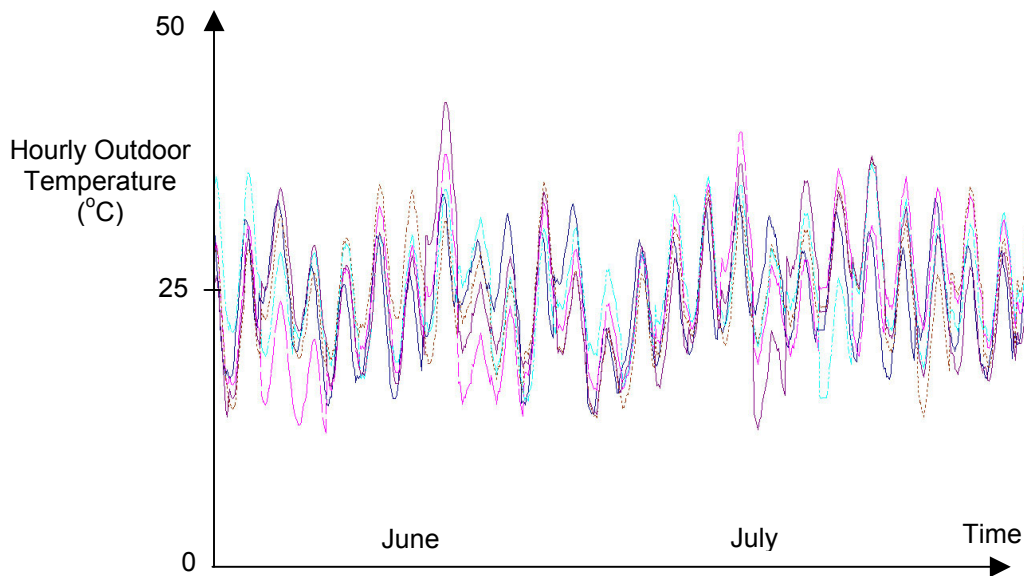


Figure 42. Five sample paths of stochastic hourly outdoor temperature for Chicago produced by the stochastic weather generation model.

5.4.2. Building energy simulation model

The heat transfer model used for estimating the building's thermal performance, including heating load, cooling load, and indoor temperature when naturally ventilated, is described in detail in Lehar and Glicksman (2004) and Arons (2000). The model takes advantage of somewhat simplified thermal analysis algorithms so as to provide results in a short amount of time. This feature enables assessment of a building's thermal performance subject to thousands of paths of climate evolution in a reasonable time period. This would not be possible with more detailed energy simulation programs such as DOE-2¹². However, the simplified building (energy) simulation model also has three important limiting assumptions:

1. Fan energy is not considered.
2. Humidity is not considered.

¹² DOE-2 is a widely used and accepted building energy analysis program that runs in DOS and requires substantial experience to use effectively.

3. The NV airflow rate is set at a predetermined, constant user-input value.

These simplifications mean that the cooling energy consumption is underestimated for *all* cooling strategies (MC, HC, and NV) due to the neglect of fan energy and humidity. The constant NV airflow rate means that heating energy is overestimated during shoulder seasons in a NV building. Also note that the constant NV airflow rate means that the model does not include design parameters such as window openings, wind pressure coefficients, control algorithms, etc. that are otherwise needed to design and determine the airflow rate of a naturally ventilated building. The neglect to consider humidity means the level of comfort of the NV building may be overstated, as high humidity may make the conditions uncomfortable even if the dry bulb temperature is at an acceptable level. These simplifications were necessary for development of the rapid-calculating building simulation program.

The building to be simulated is described by input parameters including room dimensions, window type and amount, building orientation, internal loads, air-change rate (for MC and NV strategies), insulation, and thermal mass. Only one floor of a building is analyzed, and thus results are quoted per unit area of total floor area. Conventional window typologies (i.e., single-, double, and triple-glazed windows) are simulated as a conduction resistance, or U-value, in a thermal circuit (Lehar and Glicksman, 2004). A solar heat-gain coefficient is used to model the passage of solar radiation through a conventional window. Daylighting is also analyzed in the program, and electric lighting is only used when needed to supplement daylighting.

The model can be programmed for a “mechanical,” “natural ventilation,” or “hybrid” simulation. “Mechanical” means that the building envelope is sealed and heating, ventilation, and air-conditioning systems are active. “Natural ventilation” has no mechanical means of controlling the building’s indoor thermal environment. Rather, windows are opened to allow outdoor air to flow in at a *constant, predetermined*, user input rate. Also, blinds are adjusted to attempt to moderate extremes of high and low temperatures. The indoor temperature in the “natural ventilation” scenario may become uncomfortably high. “Hybrid” is the same as “natural ventilation,” except that the

mechanical system is used when the indoor condition is uncomfortable (i.e., indoor temperature is too high). A design guideline for NV buildings is to create open floor plans with a narrow floor-plate. The building simulation assumes that the indoor-air is well mixed; thus, individual heating or cooling loads for each of the four building sides are added together to determine a final, overall load for the floor. The building simulation can also be programmed to provide separate results for each of the four sides, under the assumption that indoor air is not well mixed (due to internal partitions, for example).

Thermal mass is incorporated into the building energy simulation model, and is discussed here briefly as it is relevant to NV design strategies which depend on the innate thermal properties of the building system. Thermal mass has the effect of moderating diurnal temperature swings in a building. In the model, “high” thermal mass corresponds to a thick concrete floor and iron girder construction. “Low” thermal mass describes a light or timber-framed construction with no concrete floors. Any thermal mass is assumed to reside in the floor of the room, not the façade. Choice of insulation does not affect thermal mass.

Cooling loads, represented by enthalpy differences of the indoor air and supply air are converted to input energy (i.e., electricity) requirements using an assumed COP of the chiller equipment. The simulation is performed on an hourly basis using hourly inputs of temperature, solar radiation, and (solar) illuminance. For this research, the basic energy simulation model was modified to read in multi-year time series of weather input data and to perform calculations for the NVO and MC buildings in parallel. For the MC building, the primary results are hourly values of cooling load in units of kWh/m². For the NVO scenario, the first phase (NV mode) results are hourly values of the indoor temperature. The NVO second phase results are hourly values of cooling load in units of kWh/m². Heating loads are also calculated, but are not used directly in the real options analysis. The two variations of the building produce nearly the same results for heating loads. Differences arise primarily in the ‘shoulder’ seasons when the dampening effect of thermal mass combined with the hourly decision on whether or not to ventilate the

building for cooling is intermixed with the need for heating, as discussed further in Appendix F.

5.4.3. *Real options exercise rule*

The real options portion of the model applies the user-input decision criteria for when to exercise the option to install mechanical cooling. The decision criteria consist of three components:

- T_{max} , the maximum (hourly) indoor temperature,
- N , the total number of hours in a “sliding” assessment window, and
- n , the number of hours within the sliding window that cannot exceed the maximum temperature.

The assessment window is “sliding” in that it begins with the first N hours of the year and then advances hour by hour applying the criteria n and T_{max} , at each step. Application of these decision criteria is pictured in Figure 43. If the number of hours at or above the maximum allowable temperature exceeds the criterion, the option to install the mechanical cooling system is exercised, and the NVO building enters hybrid mode. The recorded time of exercise is the last hour of the sliding window (of size N hours) being assessed.

The number of trials, or entire runs of the model, and the number of years in each trial are user-specified inputs to the program. In the analyses conducted herein, the building energy simulation and application of decision criteria are repeated for one hundred trials, each of 10-years length. This choice is partly reflected by the amount of time needed to run a full experiment: approximately 6 hours for 100 trials of 10-years each using a 1.4 GHz processor with 512 MB of RAM and no other programs running. MIT’s Athena computing system’s “longjobs” service was used so that two people could run 6 simulations at a time (3 each).

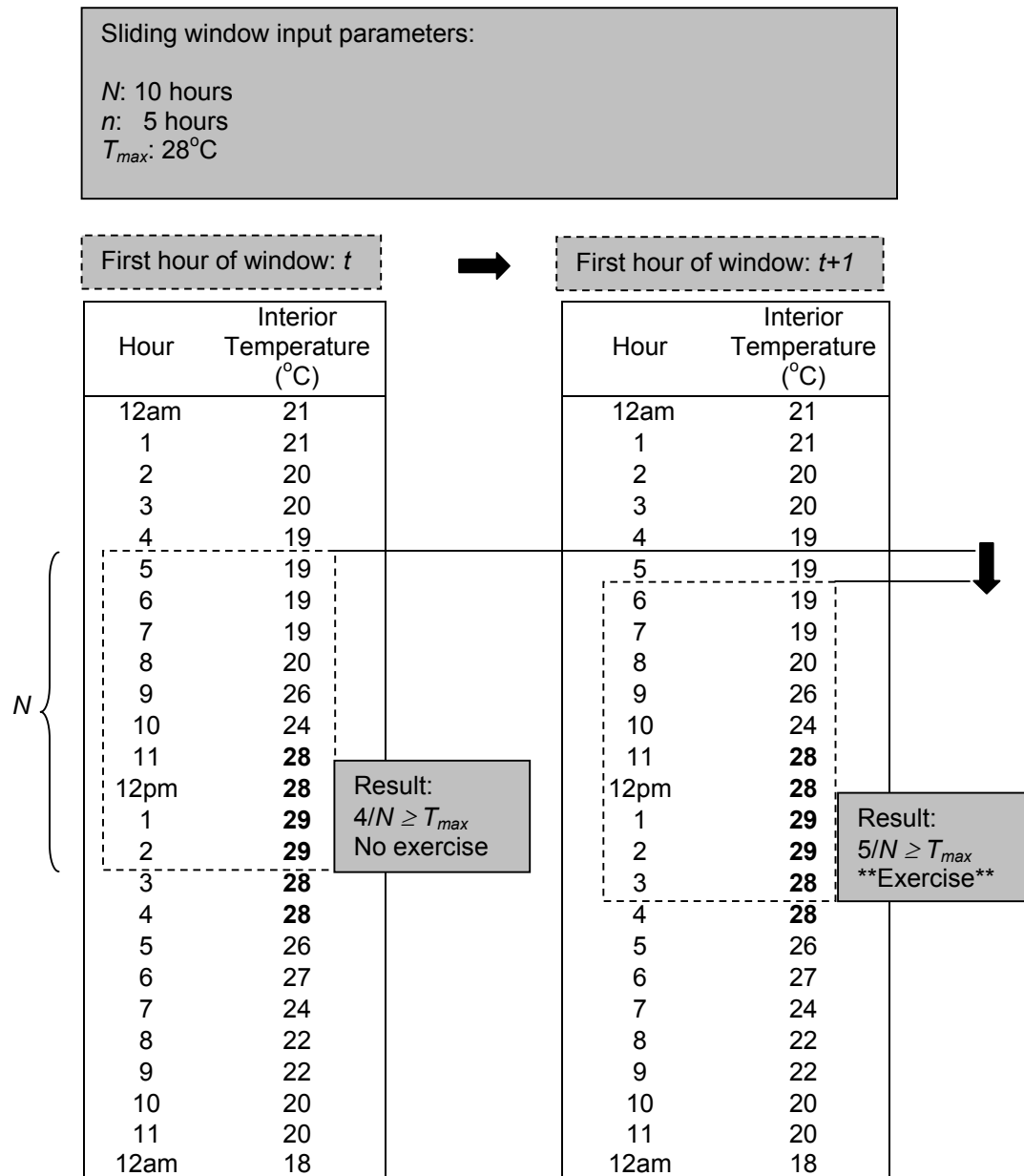


Figure 43. Illustration of the sliding window application of the decision rule. In this illustrative figure, the window is 10 hours in length and the maximum temperature is 28°C. If a maximum of 5 hours within the 10-hour window are allowed to be at or above 28°C, the option to install mechanical ventilation is exercised in the second window shown.

Choice of the maximum indoor temperature is guided by research conducted by Brager and de Dear (2000). Brager and de Dear (2000) demonstrate that office-building occupants in a naturally ventilated building are satisfied with a wider range of indoor climatic conditions. The traditional method for predicting comfort and the need for air-

conditioning is the predicted mean vote (PMV) method, as provided in ASHRAE Standard 55. The PMV method suggests that indoor operative temperature not exceed 27°C (for a dew point of 2°C). However, Brager and de Dear (2000) propose an adaptive comfort standard for naturally ventilated buildings, in which the acceptable indoor temperature for comfort is a function of the mean monthly outdoor air temperature. For example, when the mean, monthly, outdoor dry-bulb temperature is 30°C, eighty percent of occupants will be satisfied with an equivalent indoor operative temperature, as shown in Figure 44 (Brager and de Dear, 2000).

In running the real options simulations, the higher levels of allowable maximum indoor temperature shown to be acceptable in naturally ventilated buildings will be used. The model is simplified by allowing a single choice for acceptable indoor temperature (i.e., T_{max}), as opposed to making it dependent on the outdoor air temperature as demonstrated by Brager and de Dear (2000) in Figure 44. Furthermore, it is assumed that the indoor (dry bulb) temperature simulated in the building energy thermal model is equivalent to the operative temperature. Dew point temperature, or humidity, is not considered. Sensitivity analysis on the maximum allowable indoor temperature is performed, primarily to determine an acceptable threshold for NV to be successful.

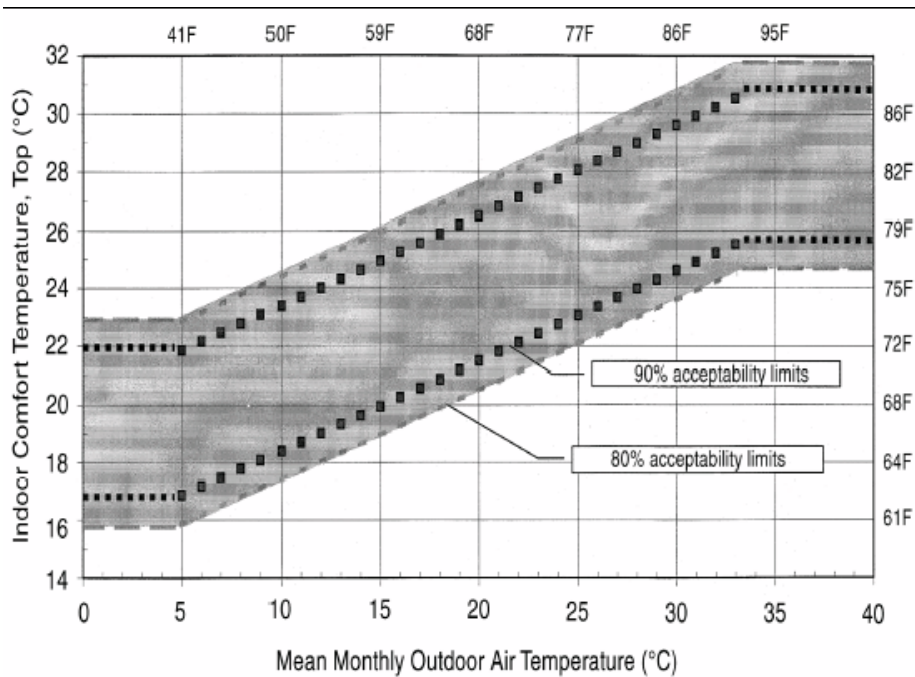


Figure 44. Acceptable indoor temperatures are a function of the mean monthly outdoor air temperature in the adaptive comfort standard for naturally ventilated buildings proposed by Brager and de Dear (2000). Source: *ASHRAE Journal*, October 2000, p. 25

5.4.4. Running the model

To run the model, the parametric description of the building, the exercise decision parameters, and the stochastic temperature model parameters are entered. The TMY2 weather data file is specified. The desired number of trials and the length of a trial (i.e., number of years) are entered. Appendix G provides a snapshot of the Excel based user interface. The simulation is ready to begin.

When a simulation is started, the two buildings (MC and NVO) are analyzed subject to the first time series of stochastic input climate data. The hourly cooling energy consumed by the MC building is determined. Likewise, the indoor temperature of the NV building is calculated on an hourly basis. If and when the comfort criteria for the NV building are violated, the NVO building becomes a hybrid building and energy results are tabulated for the remainder of the defined time period. Fourteen data points are recorded for each trial: exercise year of trial, exercise hour of year, NV heating energy consumed

until exercise time, MC heating energy consumed until exercise time, MC cooling energy consumed until exercise time, MC discounted cost of cooling energy consumed until exercise time, NVO heating energy consumed until exercise time, NVO cooling energy consumed until exercise time (this data point represents the cooling energy that would be consumed in the NVO building if it was a hybrid building from the start and is recorded for completeness; the NVO building does not actually consume cooling energy until exercise occurs), NVO discounted cost of cooling energy consumed until exercise time, MC heating energy consumed after exercise time, MC cooling energy consumed after exercise time, MC discounted cost of cooling energy consumed after exercise time, NVO heating energy consumed after exercise time, NVO cooling energy consumed after exercise time, and NVO discounted cost of cooling energy consumed after exercise time. The Java program produces an Excel spreadsheet of these results, with one row for each trial.

A Monte Carlo simulation process is used to generate results unique to the random draws of outdoor temperature. The main results of a full set of simulation trials are frequency distributions of the

- timing of installation (i.e., exercise date),
- cumulative cooling energy consumed by the baseline MC building,
- present value of cumulative MC cooling energy costs $PV[O_{MC,t \rightarrow t_2}]$
- NVO building's cumulative cooling energy consumption after exercise, and
- present value of cumulative NVO cooling energy costs $PV[O_{NVO,t' \rightarrow t_2}]$

Displaying the distribution of results gives decision-makers a picture of the range of performance possibilities. In contrast, most life cycle cost studies use the average, or expected value, of energy savings to communicate the cost effectiveness of a design. In some cases, analysis may also be done for worst and best case scenarios. However, use of an expected value, including for worst and best case scenarios, does not allow for the recognition of value that may be contained in the tails of the distribution. Within the tails of the distribution lies the information about the upside opportunity and the protection from downside outcomes.

In summary, the range of results produced by a simulation-type real options model is a key advantage over other, expected value based methodologies. Thus, results are presented as frequency distribution charts. Discussion of results focuses on the range of simulated outcomes as aided by the following statistical parameters: mean, standard deviation, minimum, 10th percentile, 90th percentile, and maximum. The 10th percentile value represents the minimum amount to spend on obtaining the flexibility with 90 percent confidence that the level of savings will be realized.

5.4.5. Estimation of exercise costs

The remainder of the analysis, including evaluation of delayed capital costs, is conducted in Excel. Recall that option value is defined as the difference in MC and NVO energy costs (if the option is exercised), plus the value in delaying capital equipment costs until the exercise date. The NVOV model provides the result for the first of those two components - the difference in cooling energy costs ($PV[O_{MC}] - PV[O_{NVO}]$). The second component, the value of delayed exercise costs, is computed in Excel for a range of possible exercise costs.

Capital equipment that may be delayed or avoided with the NVO strategy include the chiller, cooling towers, pumps, air handling units, and water pipes. The possible configurations of HVAC systems are numerous, and the specific choices of equipment will vary case by case. For example, if a heat pump system is a good candidate for the building's location for providing heating as well as cooling, very few capital equipment costs would be able to be delayed if the NVO strategy is considered. For more standard mechanical cooling systems, the components that will likely be included as part of the initial "flexible" NVO design include those for which installation at a later date would be cumbersome, time-consuming, and expensive, such as pipes, ducts, chases, fans, and diffusers. Other minimum flexibility requirements included allotted space in the mechanical room and/or rooftop space for future installation of large pieces of equipment.

RS Means Construction Cost Data 2005 provides a median value of \$92.67/m² (\$8.31/ft²) for total HVAC system costs in new construction of mid-size (4-10 story) office buildings, not including design fees and contractor profits. Based on estimates of chiller sizes required to meet the cooling loads of the baseline MC building (as will be described in Section 5.5), RS Means cost data for the relevant sized (air-cooled, packaged) chiller and the assumed floor area, \$5/m² is assumed as a minimum on the cost of capital equipment that could be delayed with the option strategy¹³. To represent a range of delay, or exercise, cost possibilities, calculations are performed for \$10/m² and results for several cases are provided for \$50/m² exercise costs, representing the delay of more than half of typical, initial *total* HVAC system costs. A generalized result will be shown for which option value can be calculated for any choice of exercise cost using the option value results for \$0/m² exercise costs (energy cost savings only) as the baseline. Exercise costs of \$0/m² represent the case where the NVO building is actually a hybrid building from the start, and MC only needs to be switched on to exercise the option. It is noted that because the option to install MC will be valuable due to other uncertainties such as future building use and market value, the option value determined in this analysis alone only represents a partial picture of the full value of the flexibility.

5.5. Input assumptions

The independent parameters in the model are numerous. Table 16 provides a list of the parameters by block of the building in which they are contained. As described, the only stochastic parameter in the model is temperature. Several choices of temperature standard deviation and trend are assessed to understand sensitivity of the results to these parameters. All other parameters are assumed to stay constant; however, in reality, other uncertain, randomly varying parameters include internal loads, discount rate, and the price of electricity. Of these, the price of electricity is the primary variable affecting

¹³ A second check on these cost estimates is done by using the rule of thumb that cooling system costs account for 10-20% of total mechanical, electrical, and plumbing (MEP) costs (Source: Huang J. Mechanical Engineer at Arup Inc. Conversation with. March 17, 2005). Mechanical (HVAC) system costs are about 1/3 to 1/2 of total MEP costs, per estimates from RS Means 2005. Combining these two figures, it can be deduced that cooling system costs range from 20-60% of mechanical (HVAC) costs. Using the RS Means 2005 figure quoted above of approximately \$90/m² for total mechanical (HVAC) costs, it is estimated that the *total* cooling system costs for new construction are approximately \$20-50/m², not including design fees and contractor profits.

option value and thus is discussed separately. Additionally the exercise cost of installing the mechanical system, if needed, may also vary somewhat from the initial estimate. Calculation of option value as a function of a range of exercise costs achieves the two goals of sensitivity analysis and understanding of the value of different levels of flexibility.

Table 16. Input parameters to the model for guiding sensitivity analysis

Model Block	Independent parameters (input by user)
Stochastic Climate Simulation	<ul style="list-style-type: none"> • Temperature standard deviation • Temperature trend
Building Energy Simulation	<ul style="list-style-type: none"> • Room and floor plate dimensions • Amount of windows • Window type (glass and blinds) • Thermal mass • Insulation (type and amount) • Shading (overhangs) • Internal loads* • COP of chiller • Air flow rate for natural ventilation
Real Options Decision Rule	<ul style="list-style-type: none"> • Maximum indoor temperature • Size of sliding window time period • Maximum amount of time allowed at or above maximum indoor temperature within sliding window • Discount rate* • Price of electricity* • Exercise cost (installation of mechanical system in NV building)*
*Indicates parameters that, although assumed to be constant, are also uncertain and (partially) stochastic in reality.	

5.5.1. Office building description

The base case building design assessed in this study is illustrated in Figures 45 and 46, and the parameters are specified in Tables 17 and 18. The building design consists of an open floor plan, narrow floor plate, and east west orientation of the long axis, in accordance with best practice passive design principles for the northern latitudes. Other energy conservation features include external sun-shading, high thermal mass, daylighting supplemented by electric lighting, interior blinds programmed to respond to solar intensity, and double-glazed low-e windows. The building simulation program models only a single floor of the building, and more advanced mechanical cooling

strategies such as radiant cooling are not modeled. The MC mode's intake rate of outdoor air is a user-specified variable. In this study, the MC flow rate of outdoor air is specified as 15 L/s so as to meet minimum fresh air requirements. If the outdoor air temperature is lower than the indoor temperature, "free cooling" is enjoyed according to this outdoor air-flow rate. (Alternatively, if the outdoor air temperature is higher than indoor temperature, this 15 L/s airflow rate must be conditioned to the appropriate temperature level before being introduced to the room.) The building simulation program does not allow dynamic variation of outdoor airflow, as in an economizer cycle; thus, the MC chiller cooling load requirements may be over estimated, the NV heating load may be greater than otherwise necessary, and NV may fail to meet comfort needs (when a higher choice of outdoor airflow rate would otherwise meet the cooling requirements).

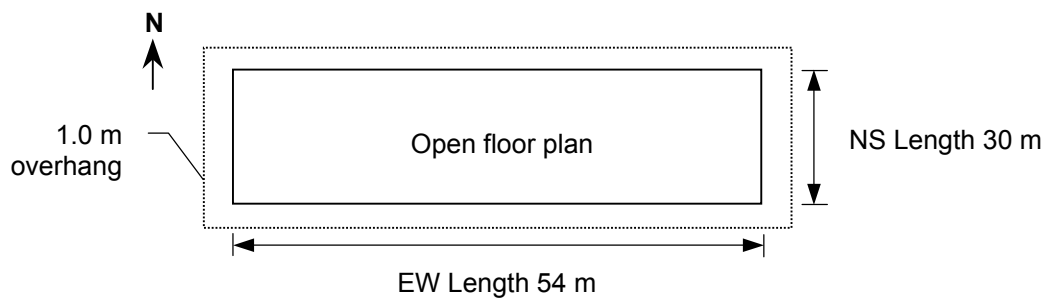


Figure 45. Floor plan of the base case building showing orientation, geometry and shading.

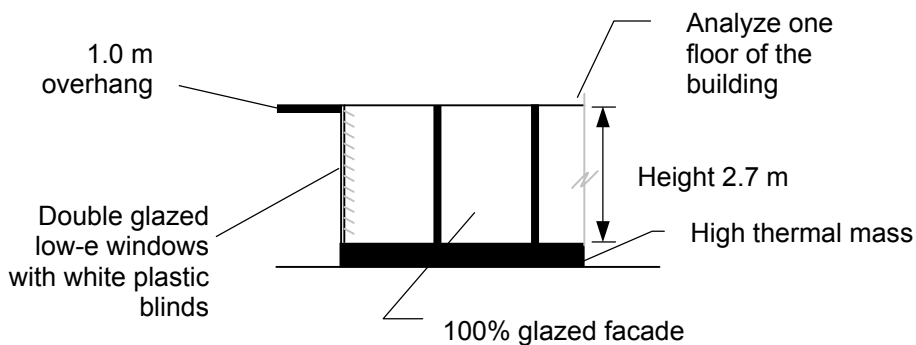


Figure 46. Section of the base case building illustrating glazing, shading (exterior and blinds), thermal mass, and height.

The building floorplate is 54m by 30m (1620 m² per floor), with the “long” façade facing the north-south directions. To model an open floor plan, the floor is modeled as two rooms, one on the south side and one on the north side spanning the entire east-west length. The room height is 2.7 m. The building is one hundred percent glazed with low-e, double-glazed windows. The manner in which airflow is created under natural ventilation conditions is not specified (i.e., could be operable windows, vents, or a combination). When the percentage of glazing is varied, the insulation parameters used are one centimeter of foam insulation. The building has a 1.0-meter external overhang around the entire perimeter to provide shading. The internal blinds are white plastic, which correspond to an assumed absorptivity of 0.38 and emissivity of 0.8. The blinds are always open at night, and they are opened and closed in accordance with solar intensity during the day.

The occupancy load is 0.1 persons/m², which equates to 162 people in the 54x30m floor plan. The equipment load is 5W/m², for a total of 8100 W for the floor plan, which is equivalent to 81 desktop computers (assuming 100 W per computer). The lighting requirement is 400 lux, which is equivalent to 0.6 W/m² and 972 W total for the floor plan if, and when, all lighting is provided by electric lights. The outdoor airflow under mechanical cooling is 15 L/s/person (minimum fresh air requirements), which corresponds to 2 ACH for the building geometry and occupancy specified. For natural ventilation, the airflow rate is one of the primary design variables that affect the success of natural ventilation in the model, with exterior shading, percent window façade, and thermal mass as other important design parameters. The base case choice of the NV airflow rate is 5 ACH, and, for cases where NV always fails, higher rates are tested. The indoor air is assumed to be well-mixed, meaning that a heating load in one portion of the floor plan (e.g., north) may be offset by excess heat (cooling load) in another portion of the floor plan (e.g., west). However, in assessing the internal temperature under natural ventilation, a temperature for each of the four (directional) areas (north, south, east, and west) is computed. Mixing of the internal air occurs only after the theoretical thermostat thermometer is read on each of the four building sides, and the mixed air condition is

then used to determine final energy balances (i.e., cooling and heating loads). Under mechanical and hybrid cooling strategies, the maximum indoor temperature is 28°C. Under all cooling strategies, the minimum allowable temperature is 16°C, below which heating is needed. The wide variation provides conservative estimates on heating and cooling energy requirements, and is indicative of a building where the occupants exhibit variable adaptation to the thermal environment. The alert temperatures, which tell the building to take action such as close windows and use heating or air-conditioning, are 18 and 26°C for heating and cooling/NV respectively.

Table 17. Geometry and component input parameters describing the base case building.

Building description			
Geometry			
	North-south length of building	30	(m)
	East-west length of building	54	(m)
	Room depth	15	(m)
	Room width	54	(m)
	Room height	2.7	(m)
	Orientation	North	---
Shading, thermal mass, and insulation			
	Thermal mass	high	---
	Overhang depth	1	(m)
	Insulation type	foam	---
	Insulation thickness	0.01	(m)
Windows			
	Window area, percentage	100	%
	Window typology	blinded double glazed	---
	Window glazing type	low-e	---
Blinds			
	Blinds width	0.025	(m)
	Blinds daytime schedule	respond to solar intensity	---
	Blinds nighttime schedule	always open	---
	Blinds absorptivity	0.38	---
	Blinds emissivity	0.8	---

Table 18. Load, control, and air flow input parameters for the base case building.

Building description			
Loads			
	Occupancy load	0.1	(people/m ²)
	Equipment load	5	(W/m ²)
	Lighting requirement	400	(lux)
Control			
	Lighting control	efficient	---
	Upper "set point" temperature on thermostat	28	°C
	Upper alert temperature telling building to take "cooling" action (open windows for NV/HC or turn on AC for MC/HC)	26	°C
	Lower alert temperature telling building to take "heating" action	18	°C
	Lower set-point temperature on thermostat	16	°C
Airflow			
	Indoor air well mixed, or not	well-mixed	
	Mechanical air change rate	15	(L/s/person)
	Natural ventilation air change rate	5	(roomfuls/hr)

5.5.2. Location(s)

Four locations were chosen for this study based on review of previous work by Spindler et al. (2002). The purpose of this study is to understand and demonstrate the ability of a back-up strategy to install MC in an otherwise NV building in climates deemed (potentially) acceptable for NV as of the current time. The purpose of Spindler et al.'s study was to assess the potential of hybrid cooling and fan-driven ventilation to reduce energy consumption, taking account of both sensible and latent loads. The building simulation program used in their study accounts for latent loads (i.e., humidity) and includes fan energy consumption, two major differences compared to the NVOV building simulator. One conclusion from Spindler et al. (2002) is that external shading provided as much savings as a hybrid cooling strategy, when compared to a reference, air-conditioned building without external shading. Addition of thermal mass also provided a

significant cooling energy savings. Thus, hybrid cooling strategies should be combined with exterior shading and thermal mass. Spindler et al. (2002) classified the results for 40 cities in five bins according to energy savings potential. Four of the cities were chosen for this study: two of the most promising cities (>20% annual cooling energy savings) - San Francisco, CA and Seattle, WA - and two of the middle category cities (5-10% annual cooling energy savings with HC) – Chicago, IL and Minneapolis, MN. The two most promising cities were chosen to study how stochastic variation in hourly temperature may affect the long-term potential of NV in locations otherwise recommended as sufficient for NV. The two medium-potential cities were chosen to understand under what conditions the option will be exercised, and to see how variation of key building parameters (air change rate for NV and percent of glazing) may affect the potential of NV to succeed over the long term under stochastic temperature variations.

5.5.3. Inputs varied in simulations

Table 19 lists the primary input parameters varied in the experiments; it also gives the base case values for each parameter.

Table 19. Base case values for the primary parameters varied in the set of experiments.

	Decision Rule			Bldg.	Climate (Temp.)	
Location	T_{max} (°C)	N (hrs)	n (hrs)	ACH for NV	σ (°C)	a (°C/yr)
SEA	29	672	224	5	2, 4	0.0038
SFO						0.0238 0.0229
CHI	29	672	336		3, 7	0.023
MSP			280			

The base case decision rule parameters were determined using the raw data of indoor temperature for the base case NVO building design produced with the building energy simulation model under average outdoor temperature conditions (i.e., TMY2 data without

random variation). The decision rule parameters were chosen such that exercise would not be induced under the expected conditions using a maximum indoor temperature choice guided by Brager and de Dear (2000), as discussed in Section 5.4.3. Note that although Brager and de Dear’s method suggests that acceptable indoor temperatures for naturally ventilated buildings are a function of the mean, monthly, outdoor air dry-bulb temperature, the NVOV model is simplified by allowing only a single choice of maximum indoor temperature. The results of the feasibility screening for decision rule parameters is shown in Table 20. The feasible values for T_{max} , n and N shown in Table 19 are those for which exercise was not induced in the base case building under non-stochastic outdoor temperature input. The results can be interpreted as either a) the minimum T_{max} for the n and N listed, or b) the minimum n for the T_{max} and N listed. The final choices for were made with the goal of uniformity among the cases.

Table 20. Screening for decision rule parameters: acceptable values of n and N for various choices of T_{max} . Values based on building simulation results for indoor temperature for the base case building design (with NV) using non-stochastic TMY2 data.

Location	T_{max} 27°C	T_{max} 28°C	T_{max} 29°C
Seattle	Minimum of $n=224$ hrs., or 1/3, of $N=672$ hrs.	---	Minimum of $n=168$ hrs., or 1/4, of $N=672$ hrs.
San Francisco	Minimum of $n=224$ hrs. , or 1/3, of $N=672$ hrs.	---	Minimum of $n=168$ hrs., or 1/4, of $N=672$ hrs.
Chicago	none	Minimum of $n=672$ hrs., or 1/2, of $N=1344$ hrs.	Minimum of $n=336$ hrs., or 1/2, of $N=672$ hrs.
Minneapolis	– Minimum of $n=336$ hrs., or 1/2, of $N=672$ hrs. – Minimum of $n=672$ hrs., or 1/2, of $N=1344$ hrs.	---	Minimum of $n=280$ hrs., or 2/5, of $N=672$ hrs.
Results can be interpreted as a) Minimum T_{max} for n and N listed, or b) Minimum n for T_{max} and n listed.			

The base case decision rule parameters for Seattle and San Francisco are a maximum temperature of 29°C, a window size N of 672 hours (i.e., four weeks), and a limit n of 224 hours (i.e., one-third of the hours in four weeks). For Chicago and Minneapolis, the limit n is increased to 336 and 280 hours respectively such that exercise was not “always” induced in the first year. It is acknowledged that the choice of 29°C is on the high end of the scale given by Brager and de Dear (2000), where the 90 percent upper limit on

comfort is 28-30°C for mean monthly outdoor temperatures of 25-30°C. As displayed in Table 21, the mean monthly outdoor temperature in the summer in all of the locations is never greater than 23°C (Chicago), even though the maximum hourly temperature ranges from 28°C to 36°C for the summer months in all four locations. Thus, the choice of 29°C is high according to the guidance given by mean monthly dry-bulb temperature; however, part of the reasoning in using a high value for T_{max} is that a separate indoor temperature is determined for each of the four building sides, and only one side need reach or exceed the maximum temperature to meet the exercise conditions of the decision rule. Actual decision rules for use in practice are a subject area for future research.

Table 21. Mean monthly dry bulb temperatures (°C) calculated from TMY2 data.

Month	Minneapolis	Chicago	Seattle	San Francisco
Jan	-12 °C	-6 °C	5 °C	9 °C
Feb	-9	-3	7	11
Mar	-1	3	8	12
Apr	7	10	11	13
May	14	15	14	15
Jun	19	20	16	17
Jul	22	23	19	18
Aug	20	22	19	18
Sep	16	18	16	19
Oct	9	14	12	16
Nov	1	6	9	13
Dec	-8	-3	7	10

The air change rate for the naturally ventilated building scenario is 5 ACH, a conservative value. The values for standard deviation σ of daily temperature for Seattle and San Francisco are 2°C and 4°C. These choices are guided by Vinnikov et al.'s (2002) analysis of observed daily temperature data for Seattle, which showed a minimum and maximum of 2°C and 4°C respectively, as discussed in Section 5.4.1. The data-derived annual growth in mean temperature a is 0.0038 °C/yr for Seattle, for both policy and no-policy conditions. For San Francisco, a is 0.0238°C/yr under no policy assumptions and 0.0229 under policy assumptions. For Chicago and Minneapolis, σ is 3 and 7 °C, and a is 0.023 °C/yr. Again, the choice σ of is guided by Vinnikov et al.'s (2002) analysis of observed daily temperature data for Chicago, which showed a minimum and maximum of

4°C and 7°C respectively, as discussed in Section 5.4.1. The effects of varying the base case input parameters are discussed throughout the Results section (5.7).

5.6. Validation

The model was validated at each step during the development process. The building simulation results for energy consumption were compared to Design Advisor results to ensure proper function of the building simulation portion of the program. The exercise rule execution was validated using the hourly raw data output (heating and cooling energy consumption, indoor temperature for NV) in Excel. Similarly, calculation of the energy consumption and energy costs were checked using raw hourly data in Excel. This process of “double-checking” was completed, making the program ready for full-scale execution of experiments using the NVOV code alone.

5.7. Results

Results for each city’s set of experiments show how sensitive a particular location is to variation of input parameters. The value of the option to install MC in a NV building, defined as the sum of the value in delayed capital costs and cooling energy savings of the option-based building relative to a baseline MC building under climate uncertainty, is given by the results presented in this section. The primary results for each simulation are exercise date, option value, and energy savings. The frequency of exercise, mean exercise date, and distribution of exercise date provides decision makers with information on the viability of NV alone to meet cooling needs. The mean option value for various exercise costs, along with its frequency distribution and 90 percent certainty level provide decision makers with investment relevant information. The model results can be compared to the estimated costs to achieve the defined level of flexibility, per the assumed exercise cost, to determine if investment should be made. For example, suppose that the results for an exercise cost of \$5/m² yield a mean option value Δ of \$7/m². This result suggests that value of the energy-saving natural ventilation cooling system with option (i.e., insurance) to install mechanical cooling in the future is \$7/m² when compared to a typical mechanically cooled building. Thus, using Eq. 5.9, the total amount to spend on the initial design and equipment costs of the NVO cooling system is

$\$7/\text{m}^2$ more than the initial costs of the baseline mechanically cooled building (less the fraction χ of equipment costs that were assumed to be delayed or avoidable in the NVO scenario, such as chiller costs). The amount of energy savings provides useful policy information when objectives of energy conservation are the primary target.

The results are presented as follows. First, a thorough discussion of the base case results for one location, Minneapolis, is provided to demonstrate the entire analytical process. Next, a comparison of base case results across the four locations is given. Following the comparison across locations are four sections covering the entire series of experiments conducted for each location. The next two sections discuss model sensitivity to temperature standard deviation and the NV air change rate – the two parameters that most significantly impact results. Next is a section on sensitivity analysis to cost calculation parameters. Finally, a discussion on uncertainty in electricity price is provided to gain a fundamental understanding of how it affects option value as defined in this study.

5.7.1. Interpreting the results – Minneapolis

The base case scenario for Minneapolis is used to illustrate the process of interpreting the results of an NVOV analysis. Note that the Minneapolis base case scenario is labeled “C” in Figure 60. The input assumptions include a 29°C maximum indoor temperature in a window of 672 hours with a 280-hour limit, NV air change rate of 5 ACH, and a daily temperature standard deviation of 3°C. In 100 10-year trials of this scenario, exercise occurred 81 times with a mean year of 3.21 (zero-base counting). Figure 47 shows the frequency distribution of the exercise year. Several observations provide insight to the usefulness of the option-based strategy. First, exercise is more likely to occur earlier in the 10-year time period than later. Although there is an equal likelihood of warm outdoor temperatures occurring in any year, the probability of delayed exercise depends on the exercise not occurring in the previous years, thus reducing the probability of late-term exercise. Second, even though exercise is more likely to occur earlier rather than later, the distribution spans the entire 10-year time period. Approximately one-third of the 80 exercise cases experienced exercise in year-5 or later. Furthermore, 20 of the cases never resulted in exercise. This delay or no exercise result means that the option value is

greatly increased by the ability to delay capital costs, as shown in Table 22 by the upper range of option value results (mean, 90th percentile, and maximum). For exercise costs of \$10/m², the mean option value for the Minneapolis base case is twice that for no delayed costs. Since the zero-exercise cost result represents energy savings benefit only, it can be deduced that the mean option value for \$10/m² exercise costs consists of equal parts energy savings and delayed capital costs.

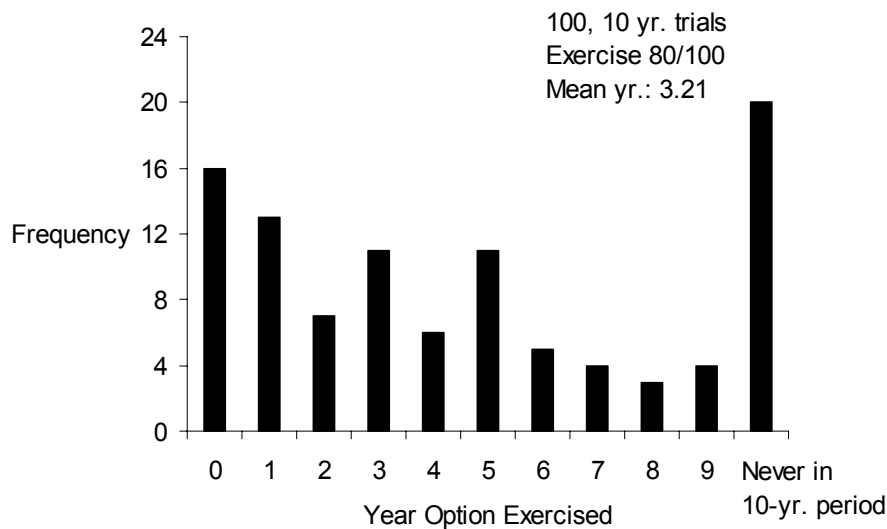


Figure 47. Frequency distribution of exercise year for Minneapolis base case.

The mean option value for zero exercise cost, which consists numerically of energy savings only, is \$3.49/m². This result indicates that, on average, it is worth \$3.49/m² to invest in a hybrid cooling system as compared to a MC building’s cooling system. Figure 48 shows the frequency distribution of option value for zero exercise costs, and Table 22 provides the minimum, 10th percentile, mean, 90th percentile, and maximum option values as a function of exercise cost. The standard deviation is 19 percent. The 10th percentile value of \$2.53/m² is the value of NVO energy savings compared to the baseline MC building that, with 90% certainty, will *at least* be realized, according to the modeling assumptions. Thus, with 90% certainty, it is worth at least \$2.53/m² to design

and construct a NVO cooling system that can be switched on for zero future costs (i.e., a hybrid cooling system).

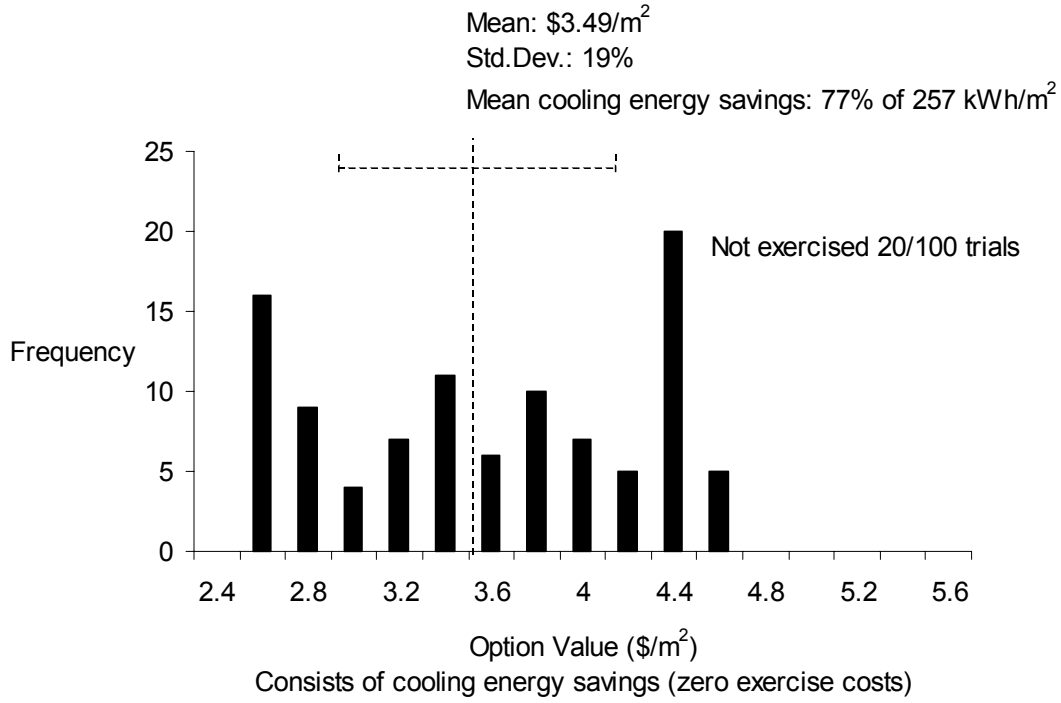


Figure 48. Frequency distribution of option value for zero exercise costs, Minneapolis base case.

Table 22. Range of resulting option values from Minneapolis base case as a function of exercise costs.

Option Value (\$/m ²) as a function of exercise cost			
Exercise Cost (current value) (\$/m²)	\$0/m²	\$5/m²	\$10/m²
Minimum	\$ 2.46 /m ²	\$ 2.46 /m ²	\$ 2.46 /m ²
10 th percentile	2.53	2.53	2.53
Mean	3.49	5.29	7.09
90 th percentile	4.39	9.38	14.38
Maximum	4.43	9.43	14.43

Introduction of exercise costs provides the opportunity to benefit from delayed capital expenditures. Thus, results from non-zero exercise cost scenarios consist numerically of the zero-exercise cost results (i.e., cooling energy savings) plus the benefit of delayed capital cost. This is illustrated by discussing the numerical results for an exercise cost of \$10/m². When an exercise cost of \$10/m² is expended on the exercise date, the frequency distribution is shifted positively, or to the right, as shown in Figure 49 and Figure 50. The value of delayed capital costs comes primarily from the twenty “no exercise” cases, as evidenced by the equivalent minimum and 10th percentile results for the two scenarios. However, value is also derived in trials for which exercise occurred; the value of the option to delay increases as the year of exercise increases. The mean option value for the \$10/m² scenario is approximately double that of the no exercise cost scenario. However, the 10th percentile values are equivalent which suggests that, with 90 percent certainty, the ability to delay capital costs is not valuable. On the other hand, the 90th percentile values indicate the potential upside of delaying capital costs – the 90th percentile option value for \$10/m² delayed (exercise) costs is approximately five times the value of a \$0/m² delayed cost design. Another observation is that non-zero exercise costs increase the standard deviation, or spread, of the distribution. The 58 percent standard deviation (Figure 49) is due partly to the low absolute value of the range of numbers and partly due to the shifting of the 20 “no-exercise” trials to the same, and higher, value. The mode that occurs at \$15.00/m² option value represents the 20 trials in which exercise did not

occur (Figure 49). There is variability within these 20 trials that is not seen in the choice of bin sizes in Figures 49 and 50.

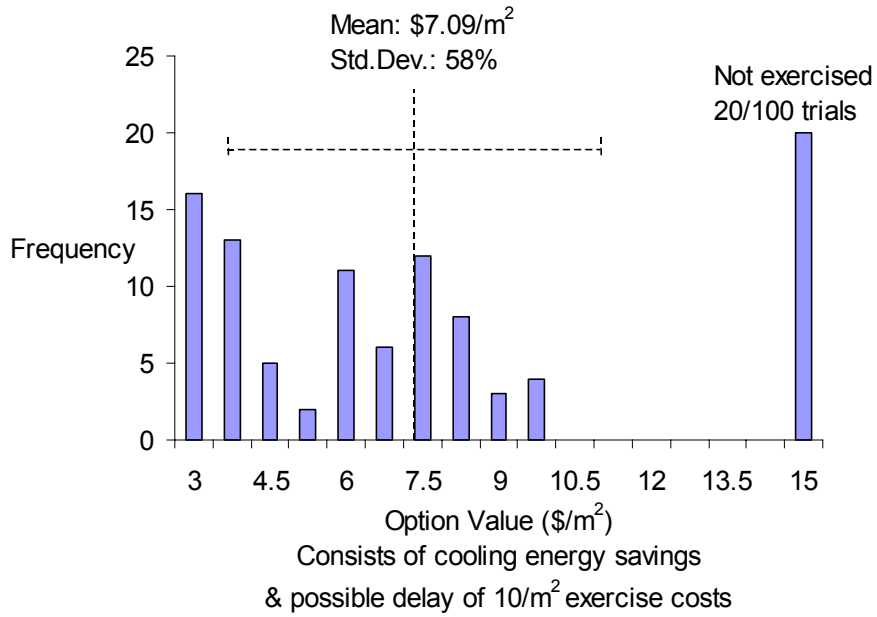


Figure 49. Frequency distribution of option value for \$10/m² exercise costs, Minneapolis base case.

Minneapolis
Base Case (C)

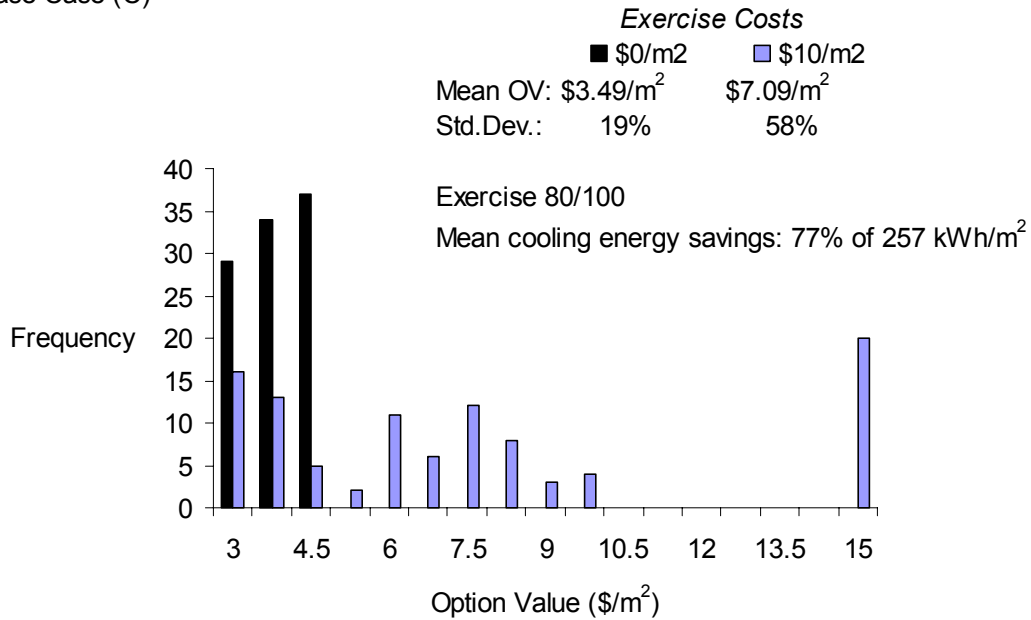


Figure 50. Side-by-side illustration of option value frequency distributions showing how results for \$10/m² exercise costs are shifted to the right of the \$0/m² results, Minneapolis base case (C).

The average cooling energy saved over the ten-year period with the NVO strategy, as compared to the MC baseline (total of 257 kWh/m²), is 196 kWh/m², or 318,000 kWh for the entire floor area. This represents a cooling energy savings of 77 percent on average. The distribution of percent cooling energy savings is shown in Figure 51. The range of cooling energy savings for all 100 trials is 140 to 257 kWh/m², or 55 to 100 percent. The result for *total* energy saved is slightly less (166 kWh/m²) than the cooling energy saved due to increased heating requirements for NV versus MC in the model.

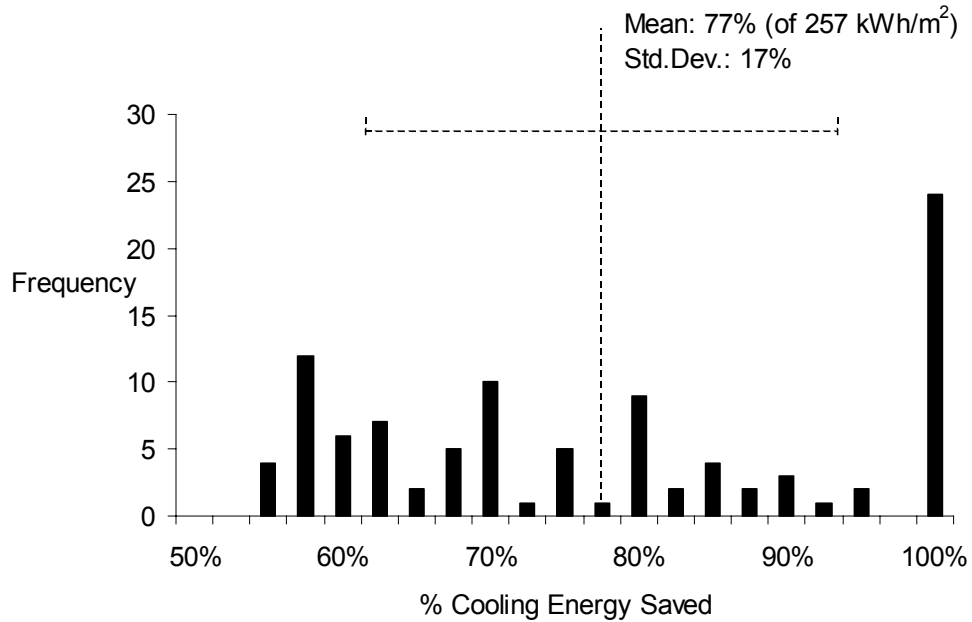


Figure 51. Range of cooling energy savings for the Minneapolis base case.

To try to increase energy savings and option value, the building’s design parameters can be altered. For Minneapolis, it was found that increasing the NV air change rate and/or reducing the percent glazed façade significantly improved the performance of the NVO building, meaning exercise was delayed and/or reduced in frequency. For example, increasing the NV air change rate slightly, from 5 to 5.5 ACH, dramatically decreases the frequency of exercise, from 80/100 to 39/100 and delays the mean exercise date to from year 3.2 to year 4.7.¹⁴ Similarly, decreasing the percent of glazed façade from 100 to 75 percent also significantly decreases the frequency of exercise (27/100) and delays the mean exercise date (year 4.3) as compared to the base case.¹⁵ Further decreasing the percent of glazed façade to 50 percent resulted in nearly no trials in which exercise occurred. Likewise, further increasing the NV air change rate to 7 ACH resulted in nearly no occurrences of exercise.

¹⁴ The NV air change rate of 5.5 ACH case is labeled “Gb” in Figure 60.

Two observations relevant to the choice of NVO exercise costs, or how much of the capital costs should be delayed, are that a) increasing the exercise cost also increases option value, and b) the incremental increase in option value decreases for each incremental increase in exercise cost. Figure 52 shows the percent increase in option value for each $\$1/m^2$ increase in exercise costs for three Minneapolis cases: the base case, the 5.5 ACH NV air change rate case, and the 75% glazed façade case. Notice that increasing the exercise, or delayed, costs increases option value. However, as indicated by the downward slopes, the percentage increase in option value *decreases* as the exercise cost ($\$E/m^2$) increases. In other words, the rate of increase in option value decreases as the exercise cost is increased. Thus, the incremental increase in flexibility budget, as given by option value, diminishes as the amount of delayed capital costs, as given by the exercise costs, increases.

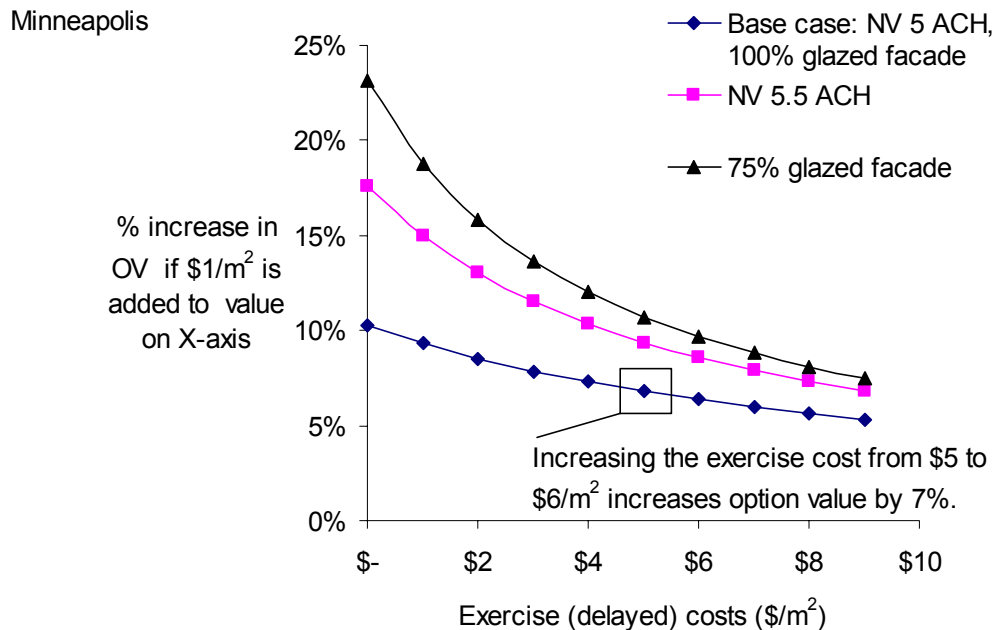


Figure 52. Rate of increase in option value as a function of exercise costs.

¹⁵ The 75% glazed façade case is labeled “Ib” in Figure 60.

5.7.2. Comparison across locations

Figure 53 shows results for all four locations for the base case building design under identical decision rule and stochastic temperature assumptions. Results are shown for exercise costs (current value) of \$0/m², \$5/m², and \$10/m². With a maximum temperature criteria of 29°C, window of 672 hours, and limit of 224 hours, Seattle and San Francisco never resulted in exercise whereas Chicago and Minneapolis always exercised the option to install MC. (As already discussed for Minneapolis and as will be shown later for Chicago, cases were produced for these two cities in which exercise did not always result.) In Seattle and San Francisco, because the simulation showed that NV succeeded for the entire 10-year period in all trials, the value of delayed equipment costs is significant. Additionally, the more costs that can be delayed, the greater the option value. The result that exercise never occurs in these locations suggest that, when considering how to spend the “option value” budget, the design team may want to consider the possibility of little attention to the flexibility to install MC, as the simulation suggests that, over the next ten years, MC will not be needed. The tradeoff would be realized in the future; if it turns out that MC is needed, greater costs would have to be incurred to exercise the option. Furthermore, the building is likely to exist well beyond ten years, and thus the risk of overheating exists beyond the assumed analysis time frame.

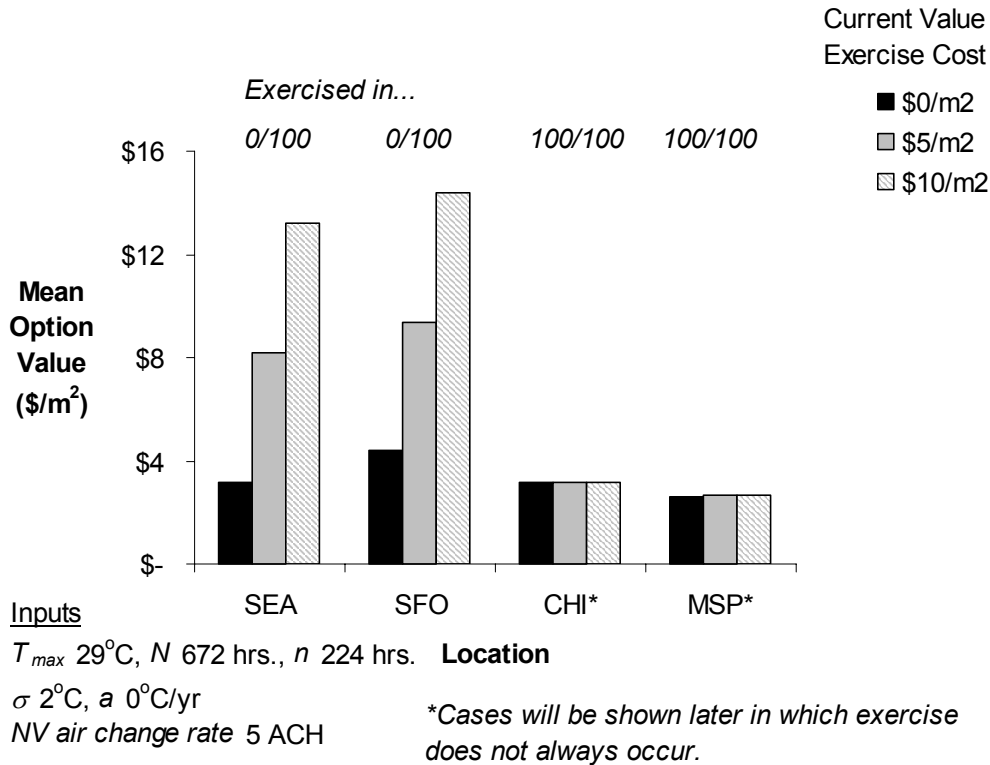


Figure 53. Comparison of results for all four locations for the base case building design under identical decision rule and stochastic temperature assumptions.

With the same decision criteria and stochastic temperature assumptions applied to Chicago and Minneapolis, the simulation provides quite different results compared to the Seattle and San Francisco, as expected. In Chicago and Minneapolis, the option was exercised in all 100 of the trials, and exercise occurred in the very first year of operation. Thus, under the input assumptions stated, hybrid cooling is necessary from the start. Because negligible benefit was realized for delayed exercise costs, the mean option values for Chicago and Minneapolis are independent of exercise costs, and the resulting values are \$3.15/m² and \$2.65/m² respectively. As discussed previously for Minneapolis and further herein for both cases, a suitable NVO scenario may be found by varying the input assumptions, particularly the building parameters and decision criteria

Greater temperature variation also means that there will be more cold days than the expected value of weather, in which case more heating will also be needed; however this result does not enter into the analysis concerned with risk of NV overheating. Designers

will want to account for the chance of greater heating needs through passive solar heating design, modularizing heating systems (expandability), or increased sizing of heating equipment.

A comparison of the average cooling energy consumed over the ten-year analysis period by the MC and NVO buildings in each of the four locations is shown in Figure 54. With the NVO strategy and the base case assumptions, San Francisco's climate results in the highest average cooling energy savings (256 kWh/m², 100%), followed by Seattle (186 kWh/m², 100%), Chicago (180 kWh/m², 52%), and Minneapolis (149 kWh/m², 59%). Figure 55 shows the average total energy consumed for both building types (MC and NVO) in all four locations. Total energy savings are less than cooling energy savings because of the increased heating energy required in the shoulder seasons with NV, as discussed in Appendix F.

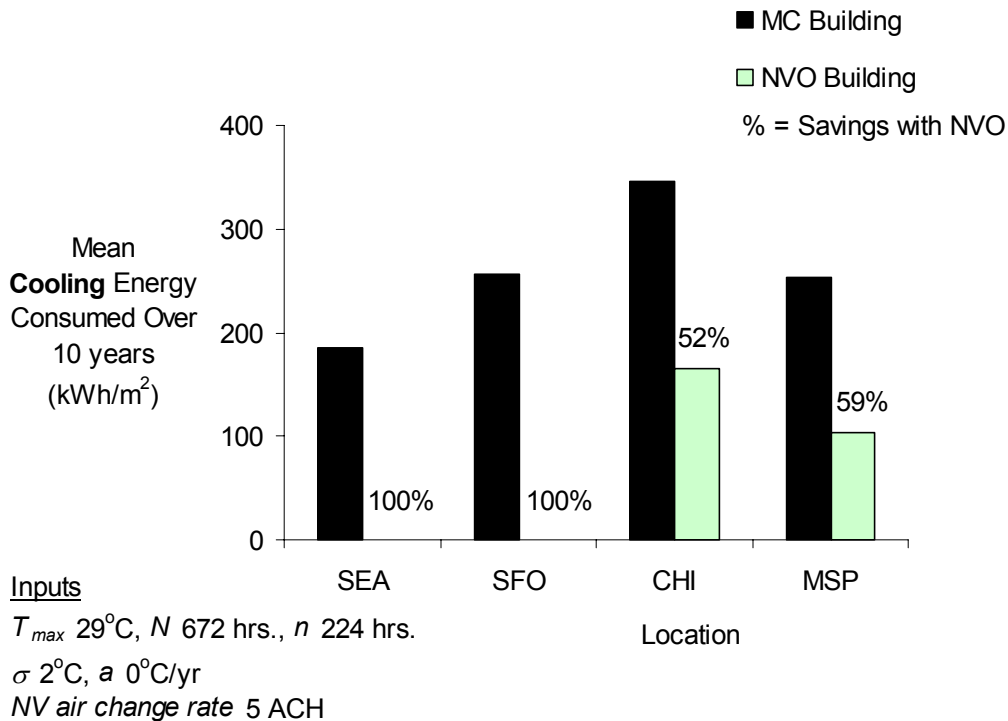


Figure 54. Comparison of mean cooling energy consumed over 10-years for MC and NVO buildings in all four locations. (Base case building design under identical decision rule and stochastic temperature assumptions.)

Note: lack of a sophisticated control system results in high heating energy for NVO building; thus, these results underestimate total energy savings with NVO.

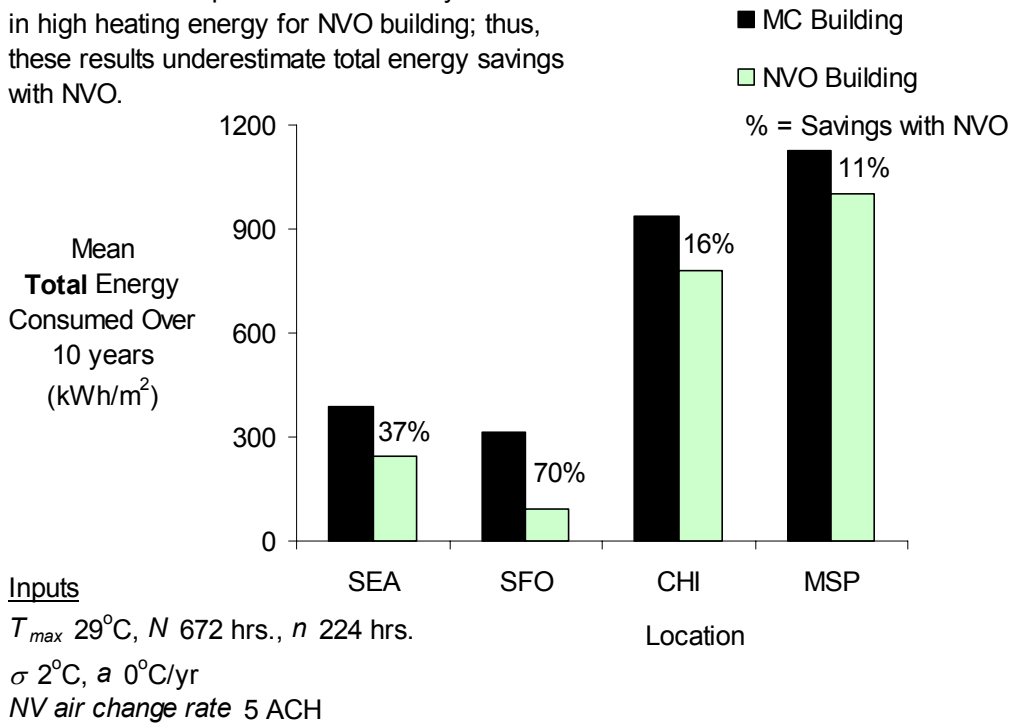


Figure 55. Comparison of total (cooling and heating) energy consumed over 10-years for the MC and NVO buildings in all four locations. (Base case building design under identical decision rule and stochastic temperature assumptions.)

The ability of the option-based strategy to protect against the risk of overheating is demonstrated by looking at the possible hourly indoor temperatures that may be experienced under NV alone. Table 23 shows maximum and 95th percentile hourly indoor temperature results for the base case building in the four cities using TMY2 climate data (i.e., zero standard deviation in daily temperature). One year of results, representing 8760 hourly data points for each of four building sides, are analyzed. The 95th percentile value reported in Table 23 represents the highest 95th percentile hourly value for each of the four building sides. The 95th percentile is the 438th highest hourly indoor temperature for a particular building side; 8322 data points are below this value. The 95th percentile temperature is the indoor temperature which, with 95 percent certainty, will not be exceeded in any given hour. The maximum hourly indoor temperature reported in Table 23 for each location is the highest temperature experienced

in any hour in any of the four building sides. As seen in Table 23, the maximum realized hourly temperatures in all locations are much higher than comfort standards allow (42°C and higher). However, these are the highest temperatures for any hour, and it may be more representative to look at average temperatures over a time period given the degree of accuracy of thermal simulation models. Furthermore, the 95th percentile values indicate that the NV building performs at least marginally well in all of the locations, with Chicago exhibiting the highest 95th percentile hourly indoor temperature at 32°C. However, the 99th percentile of indoor temperatures, representing 88 hours out of the year, are outside of comfort ranges. Table 23 provides information on the degree of extreme indoor temperature that is mitigated with the option to install MC. Tables such as Table 23 may be used to guide improvements in the design of a naturally ventilated building to show the risk of high indoor temperatures among various designs.

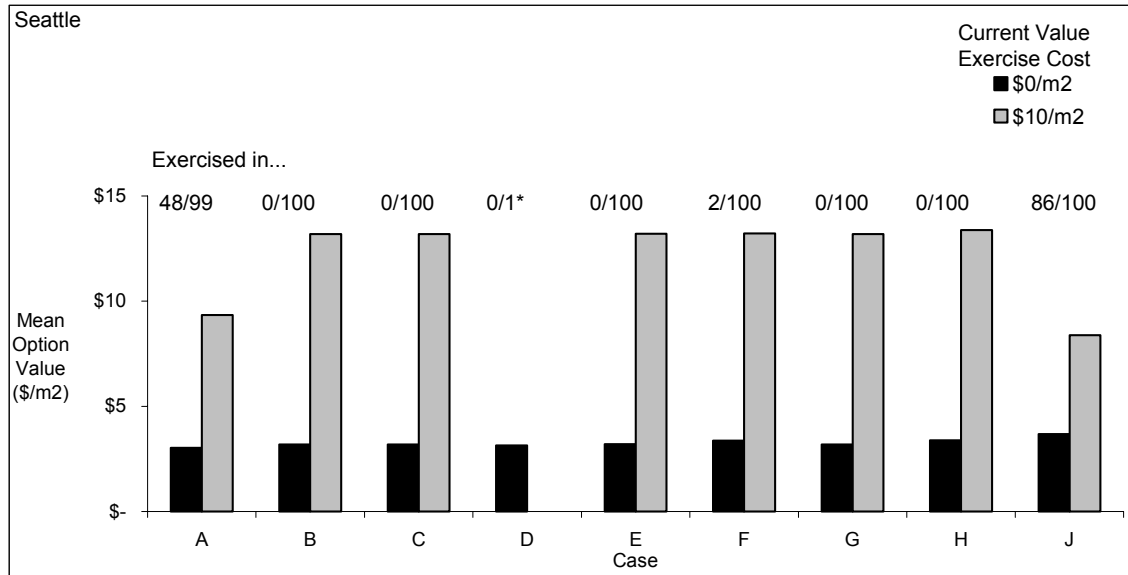
Table 23. Indoor temperature summary for NV base case building.

	Hourly indoor temperature (°C) in base case building using TMY2 climate data		
	95 th Percentile ¹	99 th Percentile ²	Maximum
Seattle	29	35	43
San Francisco	31	38	43
Chicago	32	35	49
Minneapolis	31	35	42
1. 438 hours of year at or above the 95 th percentile. 2. 88 hours of year at or above the 99 th percentile.			

5.7.3. Seattle, WA

Figure 56 shows the set of mean option value results for Seattle for various combinations of input parameters and decision criteria. The range of daily temperature standard deviation is 2-4°C, and the annual growth rate in temperature for the period 2005-2015 is 0.0038°C /yr according to the IGCM output. Natural ventilation air change rates of 5 and 10 ACH are tested. The base case decision criteria for Seattle (and for San Francisco) are a maximum temperature of 29°C, window of 672 hours, and limit of 224 hours, given by Case B. The base case is further defined by 5 ACH, a temperature standard deviation

of 2°C and a zero annual growth rate in temperature. (These are the same decision criteria as used in the comparison across all four locations shown in Figure 53). The resulting mean option value of the base case (B) is \$3.19/m² for zero exercise costs and \$13.19/m² for \$10/m² exercise costs.



	A	B	C	D	E	F	G	H	J
T_{max} (K)	300	302	302	302	302	302	302	302	302
N (hrs)	672	672	672	672	672	672	672	672	672
n (hrs)	224	224	168	224	224	224	224	224	224
ACH for NV	5	5	5	5	5	5	10	10	5
σ (oC)	2	2	2	0	2	4	2	4	4
a (oC/yr)	0	0	0	0.0038	0.0038	0.0038	0	0	0.25

*Only 1 trial because no random variation in temperature ($\sigma=0$).

Figure 56. Summary of experimental results for Seattle.

If the maximum temperature is reduced to 27°C, exercise occurs in about half of the trials (Case A), and option value is reduced to \$3.02/m² and \$9.34/m² for exercise costs of \$0/m² and \$10/m² respectively. Case C shows that a maximum temperature of 29°C is acceptable for an even shorter threshold limit of 168-hours in a 672-hour sliding window. Cases D, E, and F show that even when a higher temperature standard deviation (4°C) and annual growth rate in temperature (0.0038°C /yr) are introduced, exercise is still not induced. For the case (F) in which temperature standard deviation is increased to (4°C),

the option value is slightly higher than the base case owing to the increased cooling energy savings resulting from greater variation in temperature where NV continues to be effective (i.e., exercise still never occurs even with the higher temperature standard deviation). As will be shown in the cases of Chicago and Minneapolis, if the greater variation in temperature results in increased incidence of violation of the NV comfort rules, then option value will actually be reduced for greater variation in outdoor temperature. Cases G and H test the scenario of a NV air change rate of 10 ACH instead of 5 ACH. For the case of temperature standard deviation of 4°C, the increased air change rate results in zero incidences of exercise, whereas two occurrences of exercise occurred with 5ACH (Case H v. F). However, the low incidence of exercise with either air change rate means that option value is not sensitive to the increase in air change rate.

An unnaturally high assumption on mean temperature increase was tested on the model's ten-year time period to illustrate how climate change affects the incidence of exercise (Case J). Using a mean annual temperature increase of 0.25°C /yr, which equates to 2.5°C total mean temperature increase over the 10-year time period, and a daily temperature standard deviation of 4°C, exercise occurs in 86/100 of the cases, whereas it never occurred in the base case (Case B). Figure 57 shows the distribution of exercise dates. In contrast to cases (for other locations) in which mean annual temperature increase is not significant, the frequency distribution of exercise year is shifted towards later years in which the mean temperature is higher. Although exercise is induced with the large value of mean annual temperature increase in 89/100 cases, option value for zero exercise cost is increased by 9 percent as compared to the 4°C standard deviation case with nearly zero mean annual temperature increase and 2/100 occurrence of exercise (Case J v. F). The increased temperature provides greater savings due to increased MC load combined with NV still being able to provide for some days of cooling without the need for operating the hybrid system.

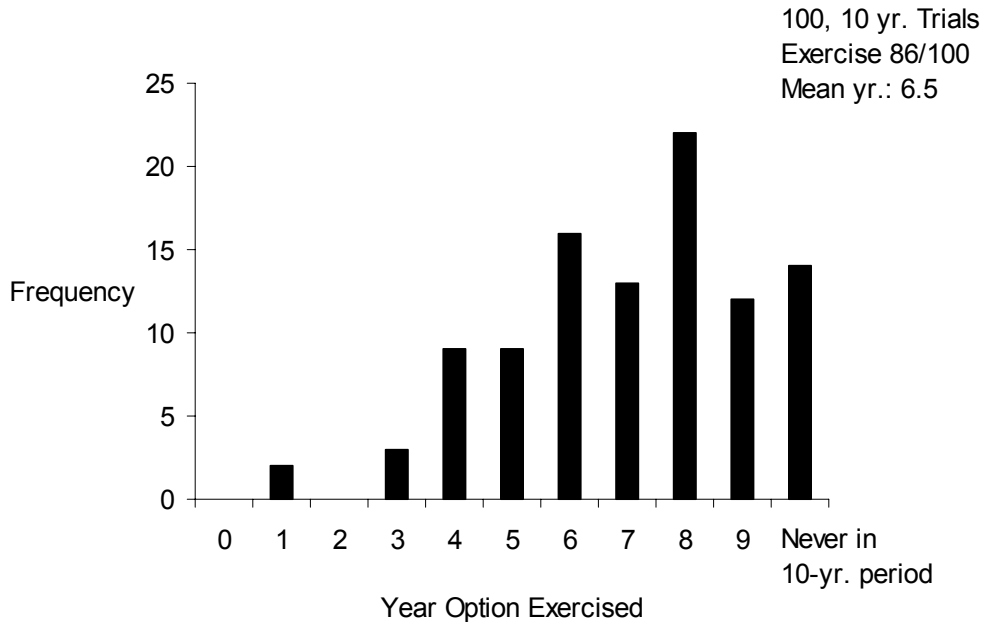


Figure 57. Frequency distribution of exercise year for Seattle under artificially high mean temperature increase scenario (Case J).

Overall, for the parameters tested in the set of simulations for Seattle, the building design is deemed suitable for natural ventilation alone to manage building cooling energy needs over the 10-year horizon. However, it is recommended that the design still consider attention to the ability to install a MC system in the future, owing to the long life of the building and possibility of variation in internal loads and/or market use of the building. The simulations suggest an option value of \$3.19/m², due to energy savings alone, and \$13.19/m² if \$10/m² in capital costs can be avoided.

5.7.4. *San Francisco, CA*

Figure 58 shows the set of mean option value results for San Francisco for the same various combinations of input parameters and decision criteria as used in the Seattle study. The one exception to the similarity of input parameters is that two values of annual growth rate in temperature were tested. The “policy” and “no policy” IGCM results for the period 2005-2015 for San Francisco’s latitude band were the only ones that varied significantly across the two scenarios. The “policy” mean annual temperature

increase was $0.0229^{\circ}\text{C}/\text{yr}$, and the “no policy” value was $0.0238^{\circ}\text{C}/\text{yr}$. The base case parameters for San Francisco are daily temperature standard deviation of 2°C , zero annual growth rate in temperature, 5 ACH for the air change rate when naturally ventilated, maximum temperature of 29°C , window of 672 hours, and limit of 224 hours. The base case (Case B) resulted in no occurrence of exercise in the 100 trials and a mean option value of $\$4.39/\text{m}^2$ for zero exercise costs, which is nearly forty percent higher than the equivalent scenario for Seattle, and $\$14.39/\text{m}^2$ for $\$10/\text{m}^2$ exercise costs.

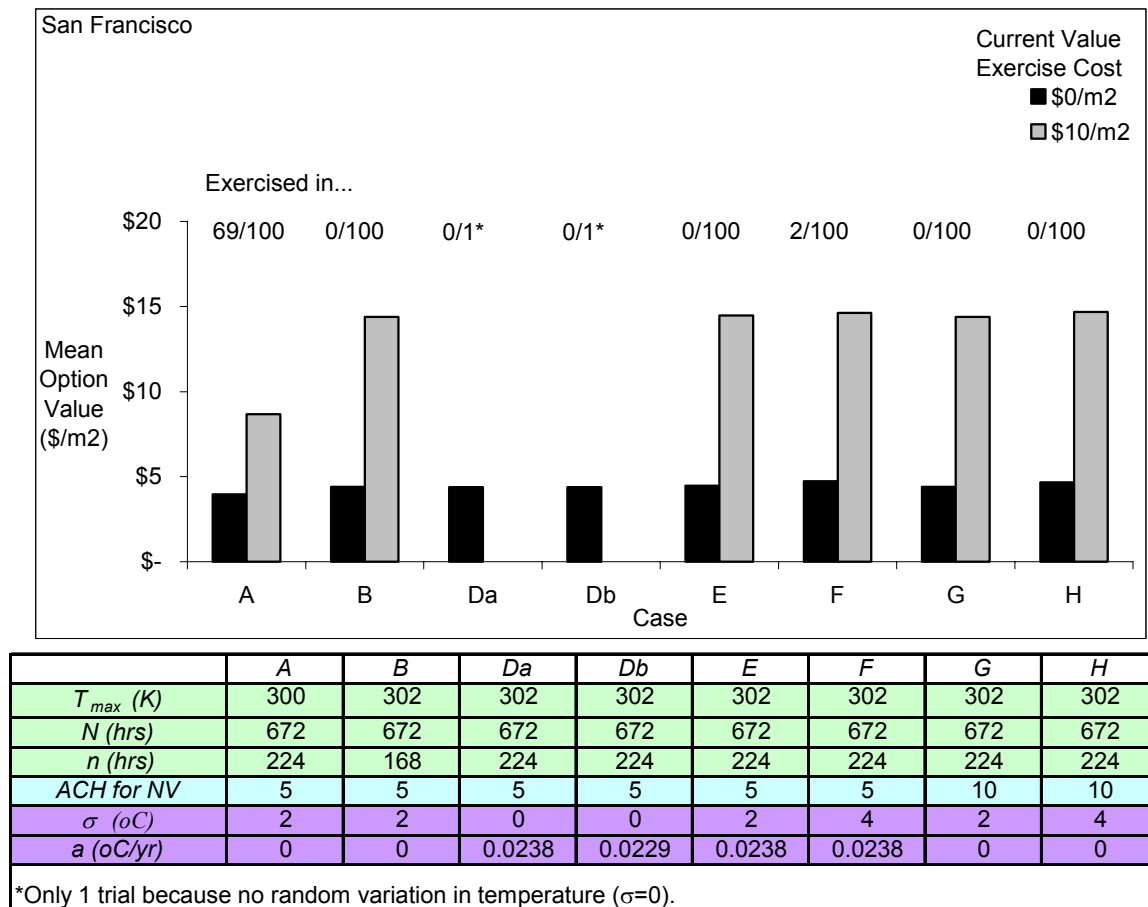


Figure 58. Summary of experimental results for San Francisco.

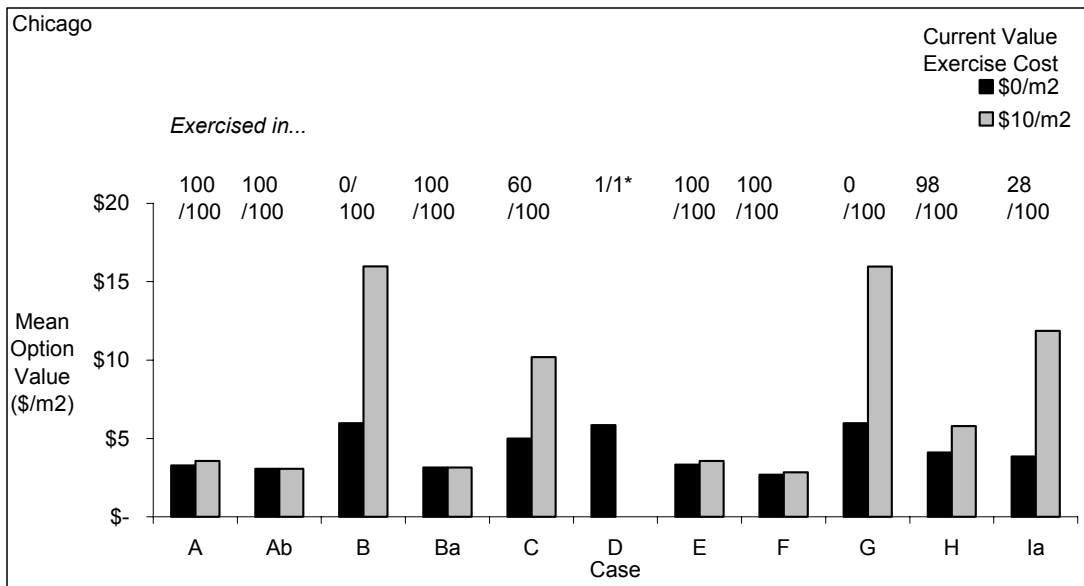
The results for the set of San Francisco cases are very similar characteristically to the corresponding results for Seattle. Exercise is induced by decreasing the maximum allowable temperature from 29°C to 27°C (Case A), and is not significantly induced by increasing the temperature standard deviation and introducing the growth rate in

temperature (Cases Da, Db, E, and F). Option value is slightly higher (2%) for the temperature standard deviation of 4°C as compared to 2°C (Case F v. E). Whereas exercise occurred in 2 out of the 100 cases with a NV air change rate of 5ACH, exercise never occurred with an air change rate of 10ACH (Case H v. F). As in the case of Seattle, San Francisco's option value is not significantly sensitive to the reasonable range of building and climate parameters tested in the set of simulations.

Overall, the building design is deemed suitable for natural ventilation alone to manage building cooling energy needs over the 10-year horizon in San Francisco. However, it is recommended that the design still consider attention to the ability to install a MC system in the future, owing to the long life of the building and possibility of variation in internal loads. The simulations suggest an option value of \$4.39/m² and \$14.39/m² for \$10/m² exercise costs.

5.7.5. *Chicago, IL*

The results for Chicago and Minneapolis are distinct from Seattle and San Francisco in that exercise is observed to occur much more frequently for the same set of decision rule parameters. Additionally, the input assumptions for temperature standard deviation are higher (3-7°C). To achieve results in which exercise did not occur one hundred percent of the time, hour limits (*n*) at a maximum temperature of 29°C in a window of 672 hours were increased to 336 and 280 hours for Chicago and Minneapolis respectively. The annual mean increase in temperature suggested by the IGCM output is 0.023°C/yr. The base case building for both locations includes a NV air change rate of 5 ACH.



	A	Ab	B	Ba	C	D	E	F	G	H	Ia
T_{max} (K)	302	303	302	302	301	302	302	302	302	302	302
N (hrs)	672	672	1344	672	1344	672	672	672	672	672	672
n (hrs)	336	224	672	224	672	336	336	336	336	336	336
ACH for NV	5	5	5	5	5	5	5	5	10	10	5
σ (oC)	3	3	3	2	3	0	3	7	3	7	3
a (oC/yr)	0	0	0	0	0	0.023	0.023	0.023	0	0	0
% glazing	1				100%					1	50%

*Only 1 trial because no random variation in temperature ($\sigma=0$).

Figure 59. Summary of experimental results for Chicago.

In Chicago, the base case parameters resulted in exercise in all 100 of the trials, with exercise occurring on average in the first year (Case A). The mean option value is \$3.27 for zero exercise costs and only slightly higher (\$3.57/m²) for \$10/m² exercise costs. Increasing the decision criteria window size to 1344 hours (8 weeks) and the limit to 672 hours (4 weeks) resulted in no occurrence of exercise (Case B). Decreasing the base case limit of 336 hours to 224 hours, the value used for Seattle and San Francisco, results in a slight reduction in zero-exercise cost option value (4%) and a one hundred percent occurrence of exercise (Case Ba). No significant difference is seen by increasing the maximum allowable temperature to 30°C for the window and limit sizes of 672 and 224 hours respectively (Case Ab).

Option value is not sensitive to addition of annual mean temperature increase ($0.023^{\circ}\text{C}/\text{yr}$) (Cases D and E). Without random realizations of temperature (Case D), energy cost savings in Chicago are much higher than with uncertainty in temperature (Case E). The cooling energy savings are approximately 40 percent lower with a temperature standard deviation of 3°C than with no variation in temperature. When the temperature standard deviation is increased further, from 3°C to 7°C , option value from cooling energy savings is further decreased (by approximately twenty percent) (Case F v. Case E). This results from exercise occurring in all trials and occurring earlier (0.2 yrs v. 0.54 yrs) in Case F (high σ) versus Case E (low σ). Increasing the NV air change rate from 5 ACH to 10 ACH results in no occurrence of exercise for a standard deviation of 3°C (Case G), but a 98% chance of exercise with the higher (7°C) standard deviation (Case H). The effect of increasing the air change rate is comparable to increasing the length of the decision rule window and limit (Case G v. Case B).

Because the building design resulted in nearly one hundred percent occurrence of exercise for reasonable climate and exercise parameters, one design variation was tested: the glazed area of the building was reduced from 100% to 50%, and 2.0 cm of foam insulation was added for non-glazed façade areas. With this building design and the base case decision rules, air change rate, and temperature standard deviation, the occurrence of exercise was reduced to 28 of the 100 trials (Case Ia). The mean year of exercise for the 28 occurrences is 4.82 (i.e., towards the end of the fifth year). The decrease in occurrence of exercise means that value is added to the option via avoided exercise costs. The mean option values for $\$0/\text{m}^2$ and $\$10/\text{m}^2$ exercise costs are $\$3.85/\text{m}^2$ and $\$11.86/\text{m}^2$ respectively.

Overall, the series of simulations indicate that the base building design in Chicago is best constructed as a hybrid cooled building as exercise occurs in nearly one hundred-percent of the cases and rather immediately. The option value for the hybrid building, from the base case input assumptions, is $\$3.27/\text{m}^2$ (zero exercise costs). However, if the façade is reduced from one hundred-percent glazed to only fifty-percent glazed and 2 cm of foam insulation are included, natural ventilation is a much more viable cooling strategy, with

exercise occurring in only 28 out of 100 cases. This revised building design is a good candidate for “natural ventilation with option” design in Chicago. The mean option value of the fifty-percent glazed building is \$3.85/m² for \$0/m² exercise costs and \$11.86/m² for \$10/m² exercise costs over the ten-year time frame.

5.7.6. Minneapolis, MN

As described in the previous section (Chicago), the input assumptions for Minneapolis include temperature standard deviation of (3-7°C), maximum temperature of 29°C in a window of 672 hours with a limit of 280 hours, and a NV air change rate of 5 ACH. Several results for Minneapolis, including the base case, were discussed in detail in Section 5.7.1. Sensitivity of results to decision criteria and stochastic temperature assumptions are primarily discussed in this section.

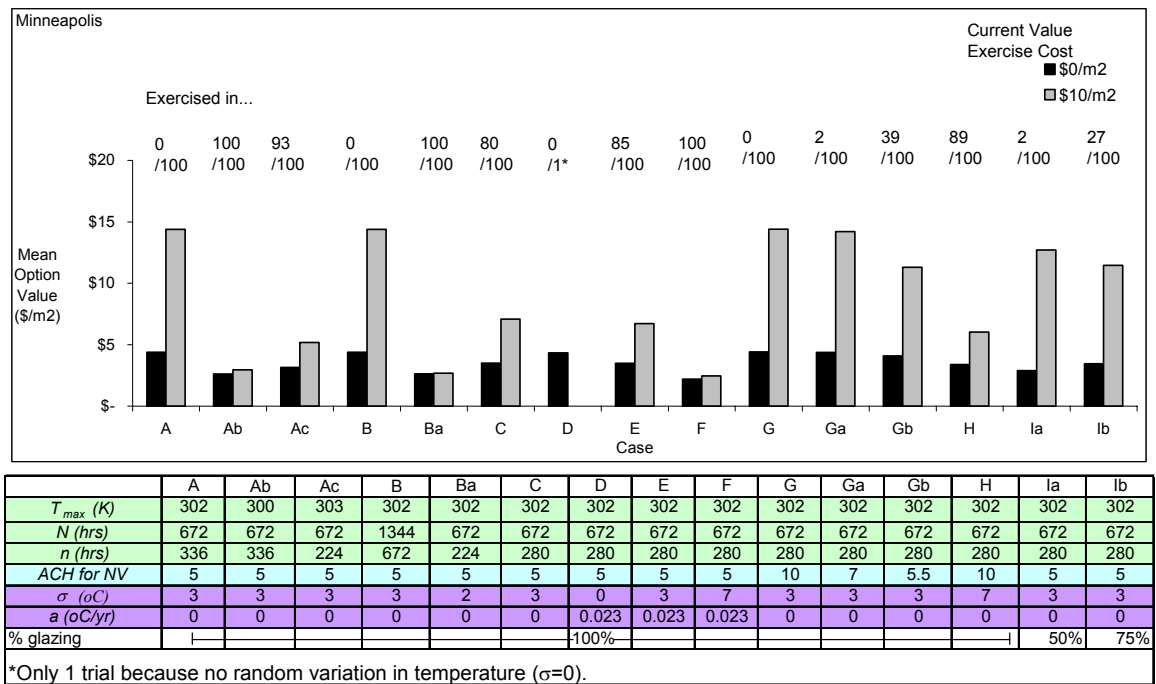


Figure 60. Summary of experimental results for Minneapolis.

In Minneapolis, the base case parameters resulted in exercise in 80 of the 100 trials, with exercise occurring on average in the fourth year (Case C). The mean option value is \$3.49/m² for zero exercise costs and \$7.09/m² for \$10/m² exercise costs. Increasing the

decision criteria window size to 1344 hours (8 weeks) and the limit to 672 hours (4 weeks) resulted in no occurrence of exercise (Case B). Likewise, increasing the limit to 336 hours within the 672-hour window resulted in no cases of exercise (Case A). Decreasing the base case limit of 280 hours to 224 hours, the base case limit used for Seattle and San Francisco, results in a one hundred percent occurrence of exercise (Case Ba) and a 25 percent reduction in zero-exercise cost option value. Increasing the allowable temperature to 30°C for the window and limit sizes of 672 and 224 hours respectively (Case Ac) reduces the occurrence of exercise from the previous case to 93/100, and thus increases option value (Case Ac v. Ba).

Option value is not sensitive to addition of annual mean temperature increase of 0.023°C/yr (Case E); however it is sensitive to the increased standard deviation of 7°C (Case F). In Minneapolis, like Chicago, an increase in daily temperature standard deviation decreases option value due to exercise occurring earlier (mean 0.4 yrs v. 3.2 yrs) and more frequent (100/100 v. 85/100) (Case F v. E). Compared to the 3°C standard deviation case (E) with the slight increase in mean annual temperature, the zero exercise cost option value of the 7°C standard deviation case (F) is 37 percent less.

Increasing the NV air change rate from 5 ACH to 10 ACH results in no occurrence of exercise for a standard deviation of 3°C (Case G), but an 89 percent chance of exercise with the higher (7°C) standard deviation (Case H.) Thus, an air change rate of 10 ACH is more than enough to provide for cooling for the 3°C standard deviation case, and greatly decreases the chance that the option will need to be exercised for the 7°C case. A slightly increased value of NV air change rate of 7 ACH still resulted in nearly no incidence of exercise for the 3°C standard deviation case (Case Ga). Furthermore, as discussed in section 5.7.1, a NV air change rate of 5.5 ACH, only 0.5 ACH higher than the base case, dramatically reduced the frequency of exercise for the 3°C standard deviation case (Case Gb). This result suggests that NV is a viable cooling strategy for the base case building design in Minneapolis if the necessary rates of airflow can be attained, which may entail using fans. Similarly, reducing the glazed area from 100 percent to 50 percent resulted in

almost no need for exercise (Case Ia), and only reducing the glazed area to 75 percent dramatically improved the viability of NV given a NV airflow rate of 5 ACH (Case Ib).

Overall, the series of simulations indicate that slight changes to the base building design in Minneapolis, such as reduced glazing and/or increased NV airflow rate, result in a viable NVO building. The original base case parameters resulted in exercise in nearly one hundred percent of the cases and early-on in the time period, thus suggesting exploration of improved design and/or a hybrid cooling strategy (instead of NVO). The revised building designs of a) seventy-five-percent glazed (with 1 cm of foam insulation) and/or b) NV air change rate of 5.5 ACH greatly reduce the frequency of exercise and delay the mean exercise date. These revised building designs are good candidates for “natural ventilation with option” design in Minneapolis. The mean option value of the seventy-five-percent glazed building is \$11.45/m² for \$10/m² exercise costs over the ten-year time frame (Case Ib). For the base case building design with a NV air change rate of 5.5 ACH, the mean option value is \$11.30/m² for \$10/m² exercise costs (Case Gb).

5.7.7. Effect of increased daily temperature standard deviation

The impact of changing the daily temperature standard deviation (σ) assumption depends on the location via the impact on exercise date. This will be illustrated by comparing the results of San Francisco and Chicago when their respective base case values of σ are increased to the applicable values of “high” σ . In San Francisco, as shown in Figure 61, increasing σ from 2°C to 4°C increases mean option value, albeit by only one-percent. Exercise never occurs in the 2°C case and occurs in only 1/100 trials in the 4°C case. This single case of exercise indicates that there is a slightly increased need to have the option in place to provide insurance against a more variable climate; however, 99% of the cases resulted in successful natural ventilation. The option value increases because the increased standard deviation results in more days of higher temperature. The higher outdoor temperature translates to increased cooling load. In San Francisco, NV is still able to provide for the increased cooling load (as evidenced by nearly no exercise), but the MC baseline building must consume more energy to meet the cooling load. Thus, for San Francisco, and other locations in which increased σ does not significantly increase

the occurrence of exercise, the upside potential of a) greater energy savings and b) possibility of avoiding capital costs increases option value.

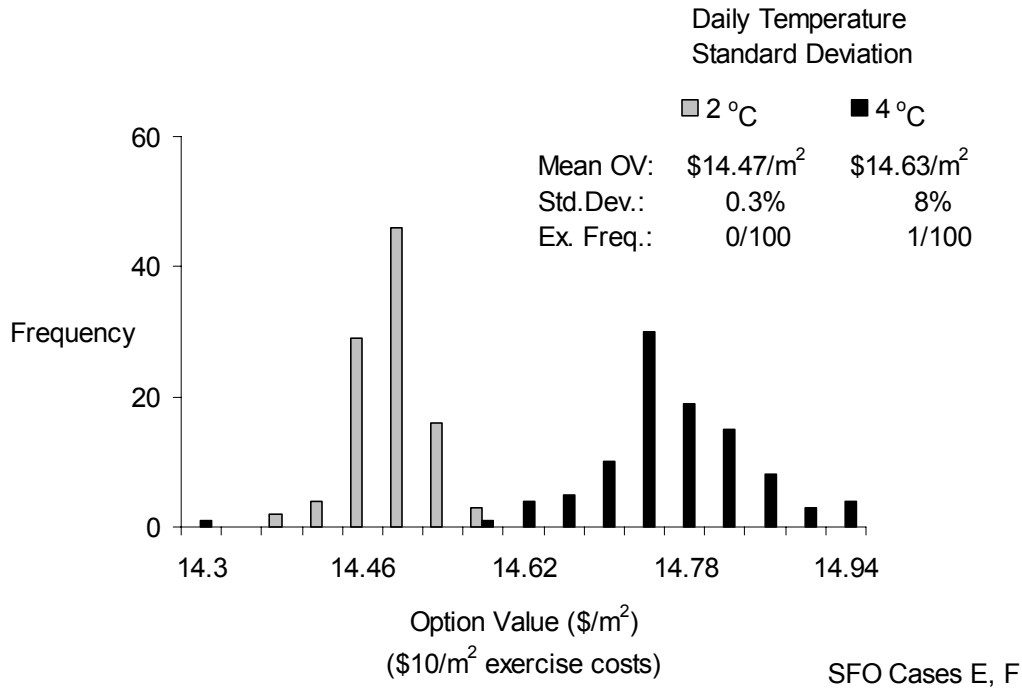


Figure 61. In San Francisco, option value increases as daily temperature standard deviation is increased for the range [2,4 °C]. Results shown for \$10/m² exercise costs.

The case of Chicago is different from that of San Francisco. In Chicago, as shown in Figure 62, when σ is increased from 3°C to 7°C, option value decreases. Exercise occurs in all trials in both cases, but the increased value of σ results in earlier exercise. The mean year of exercise is 0.2 and 0.54 for σ 's of 7°C and 3°C respectively. Chicago's climate, as applied to the base case building design, does not provide much opportunity to benefit from NV, and the greater standard deviation only results in increased frequency of higher cooling loads. In summary, whereas the value of a call option on a stock increases with increased uncertainty in stock price, the option value of the NVO strategy may either increase or decrease with increased temperature uncertainty, depending on how uncertainty impacts the exercise date.

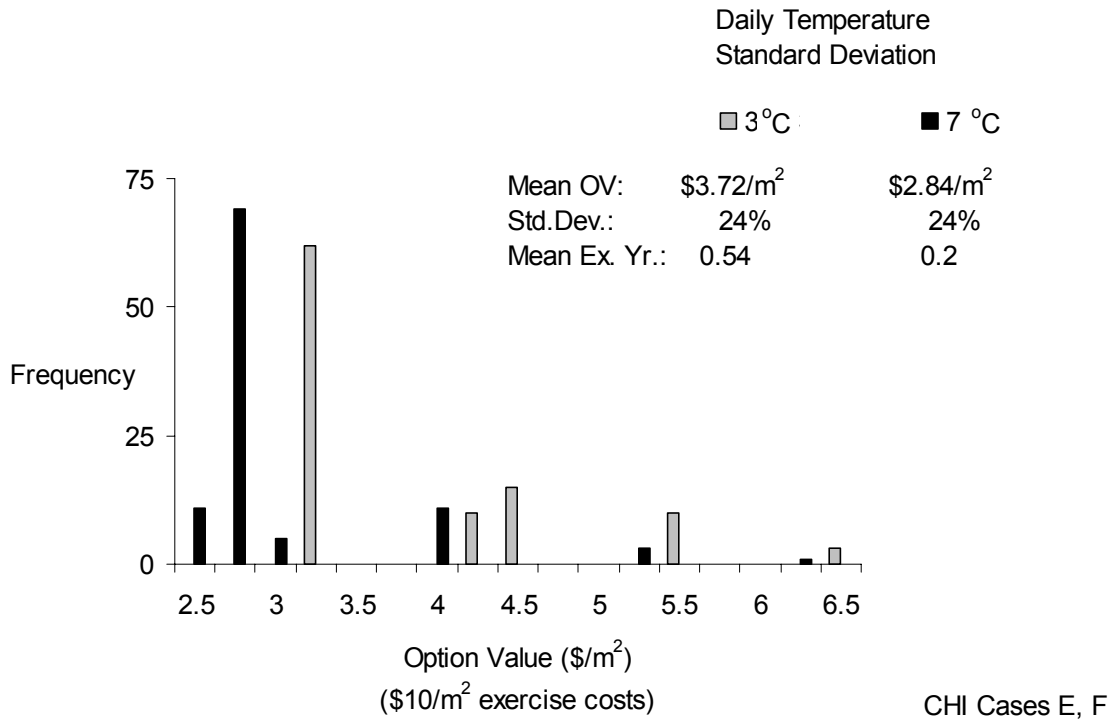


Figure 62. In Chicago, option value decreases as daily temperature standard deviation is increased for the range [3,7 °C]. Results shown for \$10/m² exercise costs.

5.7.8. Increase NV air change rate

Increasing the air change rate of NV improves the effectiveness of NV to provide for a building’s cooling needs, and thus reduces the need for exercising the option to install MC. Figure 63 illustrates the reduced chance of exercising the option in Minneapolis when the air change rate is increased from 5 to 10 ACH for a “high” σ of 7°C (Cases F and H). The exercise frequency is reduced from 100/100 to 89/100, and the mean exercise year is delayed from 0.38 years to 2.73 years. The increased air change rate provides a 54 percent increase in option value (for zero exercise costs). For \$10/m² exercise costs, mean option value increases from \$2.46/m² to \$6.02/m². This analysis ignores fan power, which may be needed to achieve the increased air change rate. For a σ of 3°C, the increased air change rate reduces the frequency of exercise from 80/100 to 0/100 (Case G v. C). Thus, option value is greatly increased (a factor of 1.3 for zero exercise costs and 2.0 for \$10/m² exercise costs).

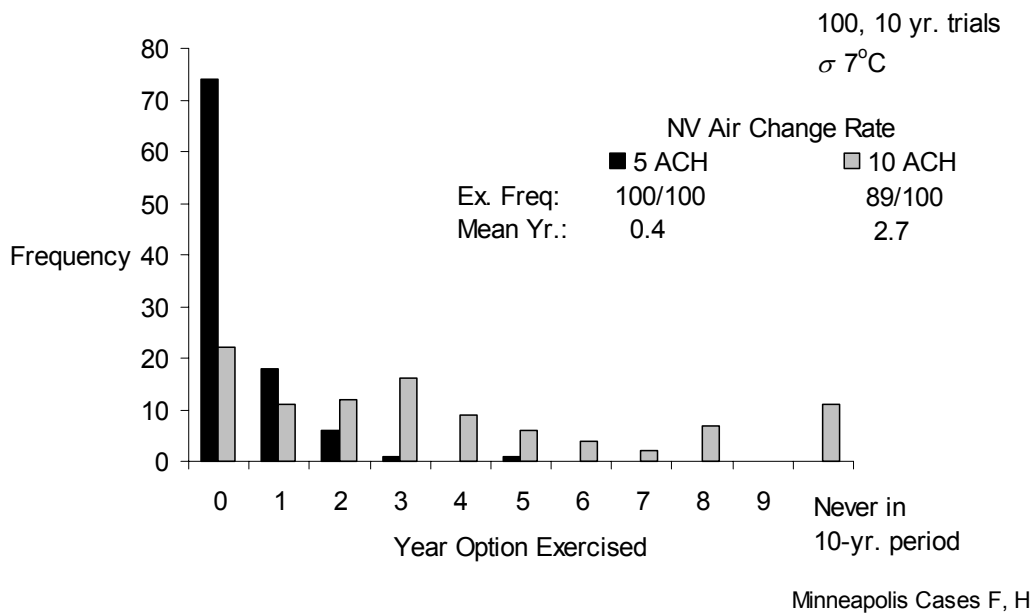


Figure 63. Increasing the NV air change rate in Minneapolis for a σ of 7°C delays the exercise date and reduces the exercise frequency.

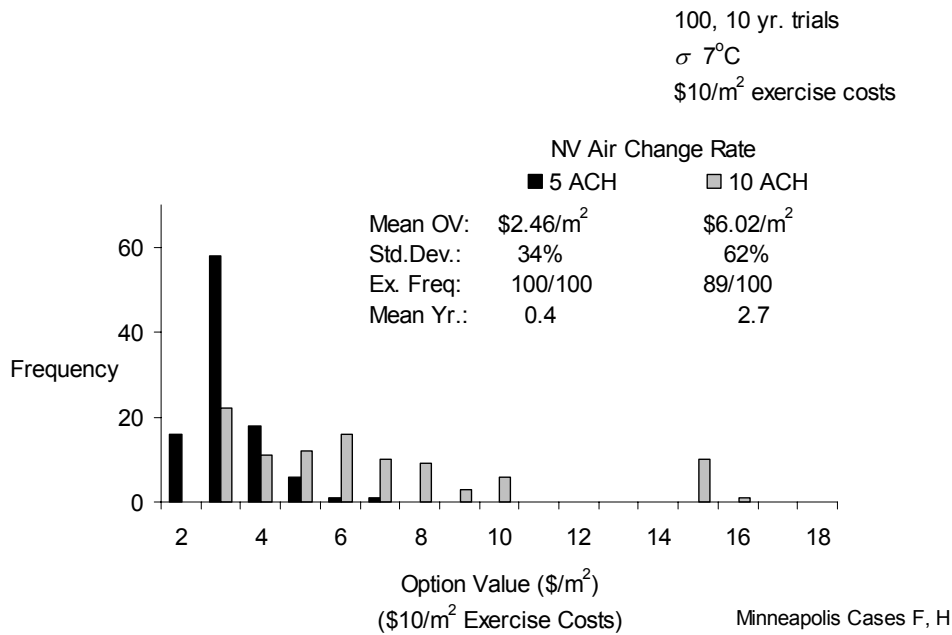


Figure 64. The increased NV air change rate thus increases option value in Minneapolis.

5.8. Sensitivity analysis of cooling energy savings' contribution to option value

Sensitivity analysis of the cooling energy savings' contribution to option value, given by Eq. 5.11, is performed for the assumed chiller COP , the price of electricity P_{elec} , and the discount rate r using results from original TMY2 data (i.e., not from stochastic evolutions of outdoor temperature). A one-year data set of MC and hybrid cooling (HC) results are produced using the building energy simulation module of NVOV with the base case building parameters. The hourly cooling load results are transported to Excel, where the present value of one year's worth of cooling energy costs is calculated using Eq.'s 5.4 and 5.5 for a range of COP , P^{elec} , and r values using the two-way data table function in Excel. Two timeframes are analyzed: 10-years and 20-years of annual cooling energy payments. The entire timeframe's present value of cooling energy costs is calculated using the annuity formula

$$PV_{T_{yrs}} = AF_{T-1}PMT + PMT \quad (5.16)$$

where AF is the annuity factor and PMT is one-years worth of cooling energy costs, or $PV[O]$ for $t = 0$ to 1-year in Eq. 5.5. The annuity factor is calculated as

$$AF = (1 - (1+r)^{-(T-1)})r^{-1} \quad (5.17)$$

The annuity factor (AF) is calculated for $T-1$ years because the present value of the first payment is already reflected in the present value calculation of one year's of energy costs (from Eq.'s 5.4 and 5.5).

A wide range of values is tested for each parameter: COP [2.5-5], P_{elec} [0.04-0.15 \$/kWh], and r [5-15%/year]. The base case values are 3, 0.08, and 10% for COP , P_{elec} , and r respectively. Assuming two limiting cases for the timing of exercise produces bounds on the sensitivity of the cooling energy savings portion of option value to these parameters. The "no exercise" bound on cooling energy savings option value is given by the MC cooling energy costs, as they represent the savings of successful NV for the entire

time-period. The “immediate exercise” bound on cooling energy savings’ contribution to option value is given by subtracting HC cooling energy costs from MC cooling energy costs, as the NVO building would be in HC mode from the start if exercise occurred immediately. Variation in (cooling energy cost savings) option value from variation in temperature is not reflected in these results.

Cooling energy cost savings increase directly (i.e., linearly) with changes in price of electricity P_{elec} and decrease directly with increases chiller COP . Thus, a percent change in P_{elec} or COP corresponds to an equivalent percent change in present value of cooling energy cost savings, with the sign of the change depending on the parameter. Although cooling energy costs do not change linearly with changes in the discount rate, the results are able to be generalized. A 100 basis point increase in the discount rate (i.e., one percentage point), results in a 4 percent decrease in the present value of ten-years of MC costs and a 1 percent decrease in ten-years of HC costs. The exception for MC costs is Minneapolis, where MC costs only decreased by 1 percent, instead of 4 percent.

Table 24 provides base case, minimum, and maximum 10-year cooling energy cost savings for “no exercise” and “immediate exercise” assumptions for the four cities. The former represents the full savings of MC cooling energy costs, as the building always exists in NV mode. The latter represents the cooling energy costs savings of a HC building versus a MC building. Notice that the “no exercise” base case results are comparable to NVOV simulation mean results for no-exercise cases, for example Seattle “B”, San Francisco “B”, Chicago “B”, and Minneapolis “A.” Slight differences are apparent because the NVOV results include random temperature, whereas the results in Table 24 are from TMY2 data without variation. Appendix E provides charts of an example sensitivity analysis for Seattle.

Table 24. Sensitivity of PV of ten-years of cooling costs to calculation parameters

<i>Values of COP, P_{elec}, and r</i>	“Never exercise” Cooling energy cost savings (\$/m ²) NV v. MC ^{1a}			“Immediate exercise” Cooling energy cost savings (\$/m ²) HC v. MC ^{1b}		
	<i>Minimum Result²</i>	<i>Base Case³</i>	<i>Maximum Result⁴</i>	<i>Minimum Result²</i>	<i>Base Case³</i>	<i>Maximum Result⁴</i>
Seattle	\$0.78/m ²	\$3.11/m ²	\$8.63/m ²	\$0.60/m ²	\$ 2.49/m ²	\$ 7.21/m ²
San Francisco	1.07	4.29	11.90	0.78	3.28	9.58
Chicago	1.46	5.84	16.19	0.76	3.47	10.72
Minneapolis	1.07	3.65	8.45	0.63	2.16	4.99
Cooling load/cost results from base case building with TMY2 data. 1a. Calculated from MC cooling energy costs. 1b. Calculated by subtracting HC cooling energy costs from MC cooling energy costs. 2. Minimum result inputs: COP 5, P _{elec} 0.04\$/kWh, r 0.15/yr 3. Base case result inputs: COP 3, P _{elec} 0.08\$/kWh, r 0.10/yr 4. Maximum result inputs: COP 2.5, P _{elec} 0.15\$/kWh, r 0.05/yr						

5.9. Sensitivity analysis of delayed costs’ contribution to option value

Calculation of the delayed or avoided capital costs’ (i.e., exercise costs) contribution to option value, given by Eq.’s 5.10-14, depends on the assumed time at which costs are incurred if “no exercise” results, the rate of inflation, and the discount rate. Additionally, if there is a cost penalty to future construction, it can be modeled by increasing the variable that represents inflation. The Minneapolis base case (C) results are used to discuss sensitivity of delayed or avoided capital costs to these assumptions. The Minneapolis base case was discussed in detail in section 5.7.1, and important results to this analysis include exercise in 80 of 100 trials, and a mean exercise year of 3.21 (i.e., in the fourth year).

To begin with, consider the assumed year at which delayed costs are incurred if “no exercise” results. All of the previous analyses assumed that the exercise costs were completely avoided if “no-exercise” resulted in the 10-year simulation. However, 10-years is a short time period within the total life of a building, which is likely to be at least 30-years, and exercise may occur some time after 10-years. Figure 65 shows sensitivity

of the Minneapolis Case C results to the assumption on the year in which exercise costs are paid, with years ranging from 10-1000. A lower bound on the delayed capital cost contribution to option value is given by the assumption that, even if a 10-year simulation results in “no exercise,” the option will be exercised at the end of the analysis period (year-10). An upper bound, as assumed throughout the analysis, is that the option is never exercised if “no exercise” is the result of the simulation. The upper bound is given by assuming that the exercise costs are incurred in year 100 or more, as they essentially represents complete avoidance of capital or exercise costs because of the discount rate. As seen in the graph, the magnitude of the sensitivity increases for increased exercise cost. However, the percent difference of the value of the delay portion of the option is constant across exercise costs – 35 percent increase for year 1000 (i.e., complete avoidance) versus year 10 (i.e., pay in year-10 even if “no exercise” results). Note that these assumptions only apply to 20 of the trials for the Minneapolis base case, as the option was exercised within the 10-year simulation in 80 of the 100 trials.

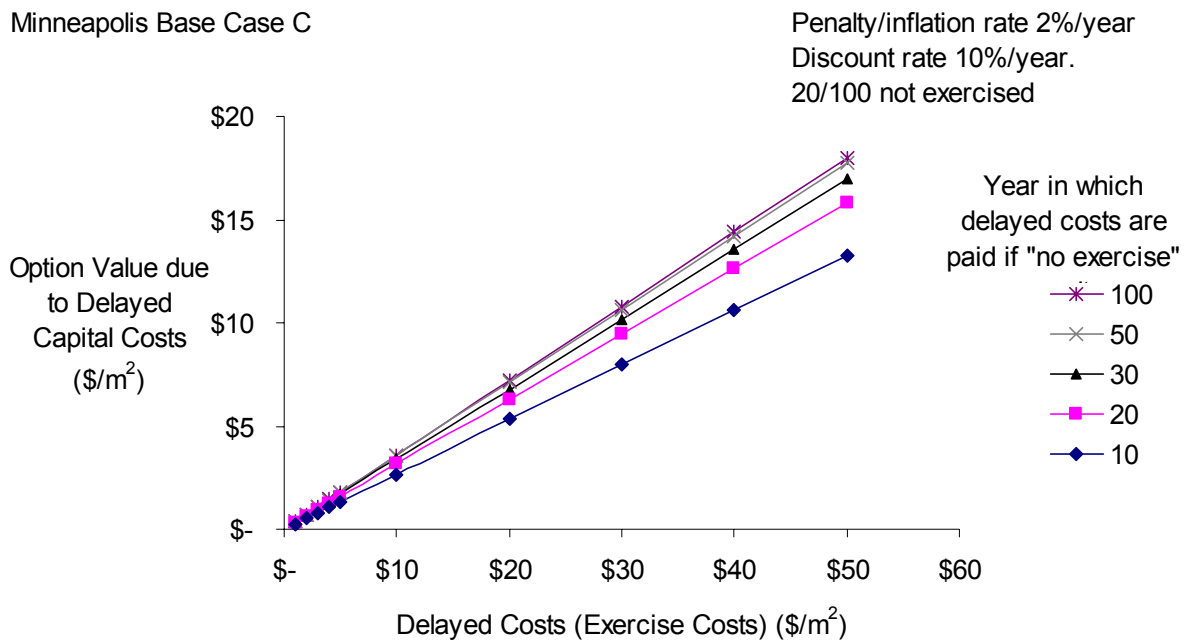


Figure 65. Sensitivity of benefit of delayed costs to assumed year at which they are incurred in “no exercise” trials.

Sensitivity of the delayed capital costs portion of option value to the assumed annual rate of inflation and/or cost penalty (r_i) is shown in Figure 66 for the Minneapolis base case. In all previous analyses, r_i was assumed to be 2 percent per year. Values of r_i ranging from 2-12 percent annually are tested in the sensitivity analysis. In this analysis, it is necessary to assume that exercise costs are paid at the end of year-10 in the 20/100 “no exercise” cases because an assumption of complete avoidance results in large negative numbers for the upper range of r_i . The assumed discount rate is 10 percent per year, as in previous analyses. As seen in Figure 66 for an r_i of 10 percent, when the inflation-penalty rate is equal to the discount rate, the option value of delaying costs is zero. Furthermore, if the inflation-penalty rate is greater than the discount rate, no benefits are realized, as costs are growing faster than they can be discounted (e.g., see r_i of 12 percent in Figure 66). Increasing the year that “no exercise” exercise costs are paid further increases the loss if the inflation-penalty rate is greater than the discount rate. The effect is the opposite if the inflation-penalty rate is less than the discount rate.

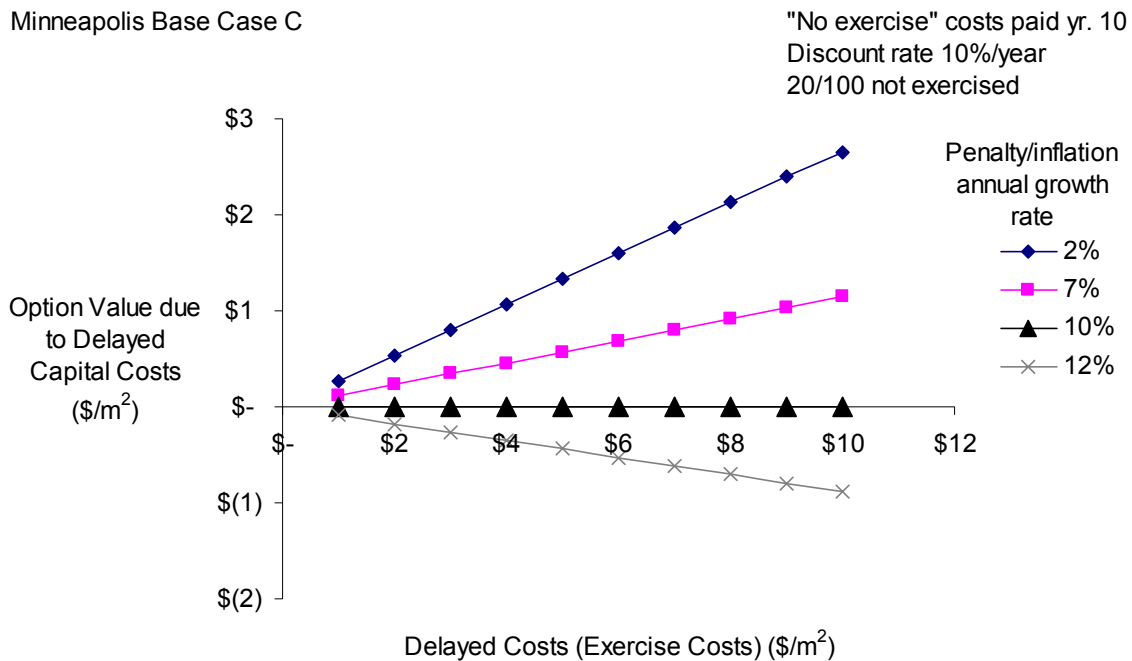


Figure 66. Sensitivity of benefit of delayed costs to the rate of inflation, which may also be interpreted as a penalty on future construction.

The option value due to delayed capital costs increases as the discount rate is increased, all else constant, as shown for the Minneapolis base case in Figure 67. Discount rates ranging from 5-15 percent annually are assessed. The assumed inflation-penalty rate r_i is two percent annually, and it is assumed that exercise costs are paid at the end of year-10 for the 20/100 “no exercise” trials. A discount rate of 10 percent per year was used for all previous analyses in this study. For the Minneapolis base case, increasing the discount rate from 10 to 15 percent per year increases the delay portion of option value by 39 percent. This is because the inflation-penalty rate only grows the exercise costs at 2 percent per year, and thus a higher discount rate results in a greater relative rate of increase in the cost savings benefit of delaying capital costs. Reducing the discount rate from 10 to 5 percent per year decreases the delay portion of option value by 55 percent. Additionally, increasing the assumed time at which exercise costs are paid for the “no-exercise” trials further increases the delay option value for all choices of discount rate, as long as the discount rate is greater than the assumed inflation-penalty rate.

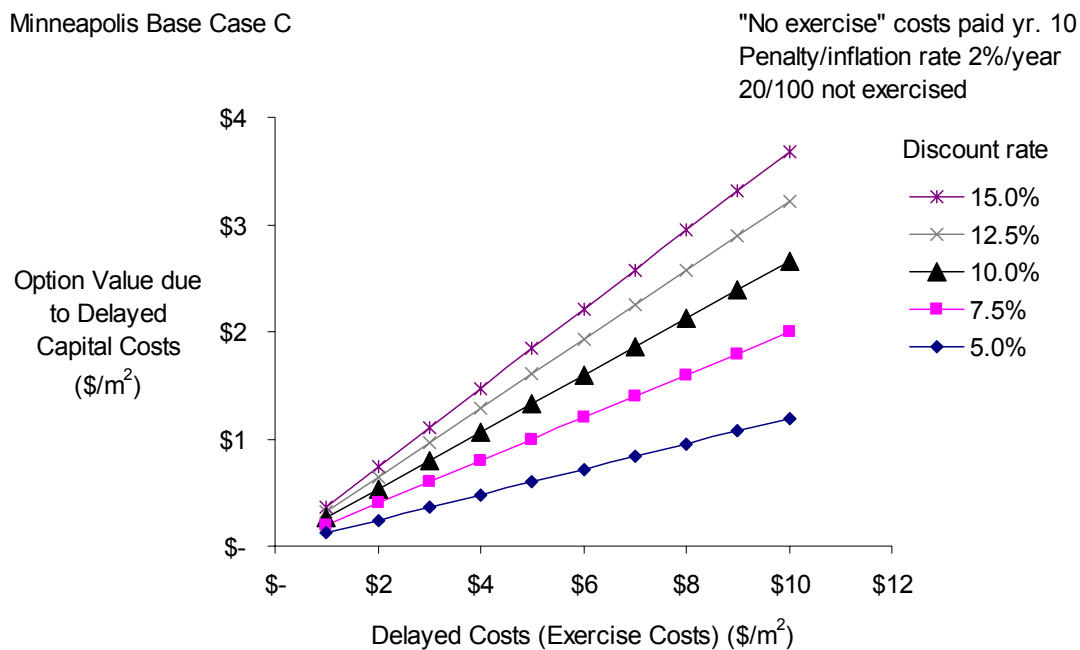


Figure 67. Sensitivity of benefit of delayed costs to the discount rate.

5.10. Impact of stochastic electricity prices

In the model presented thus far, a single, non-stochastic price of electricity is used to value the cooling energy savings portion of option value. More complex rate structures and uncertain spot prices of electricity are not considered. Additionally, the decision to exercise the option to install mechanical cooling is not a function of electricity price (i.e., cooling energy costs); rather, the decision rule is a function of the simulated indoor temperature of the NVO building, which is partially dependent on stochastic outdoor temperature as an input. This section describes the dependence of option value (i.e., cooling energy savings) on electricity price and explains the nature of uncertainty in electricity prices. Next an argument is made as to how inclusion of uncertainty in electricity price would increase the value of the NVO strategy, given that uncertainty in outdoor temperature is already considered in the current model and that uncertainty in electricity prices primarily translates to the possibility of price spikes, or high price realizations. The discussion continues with a description of how the correlation between outdoor temperature, electricity prices, and a building's cooling loads might be reconciled within an options framework that would include the cost of cooling energy in the decision rule for installing or operating a MC system.

Cooling energy costs are a linear function of electricity prices per equation 5.4, and Figure 68 shows the sensitivity of the cooling energy cost savings for the Minneapolis base case to a single choice of electricity price (\$/kWh) applicable to all hours and years in the simulation. In the real options literature, the volatility of an uncertain variable impacts the value of an option, *if* that uncertain variable's outcome impacts the decision rule for exercise. In the NVO scenario, uncertainty in electricity prices does not affect the decision rule for installing MC; the decision is made according to thermal comfort criteria. Thus, the value of the option to install MC does not depend on the volatility of electricity prices in the *traditional* sense of determining whether to exercise or not. However, the building owner is protected from downside outcomes of electricity prices (i.e., high prices), and thus high cooling energy costs, whenever the building can be operated in NV mode.

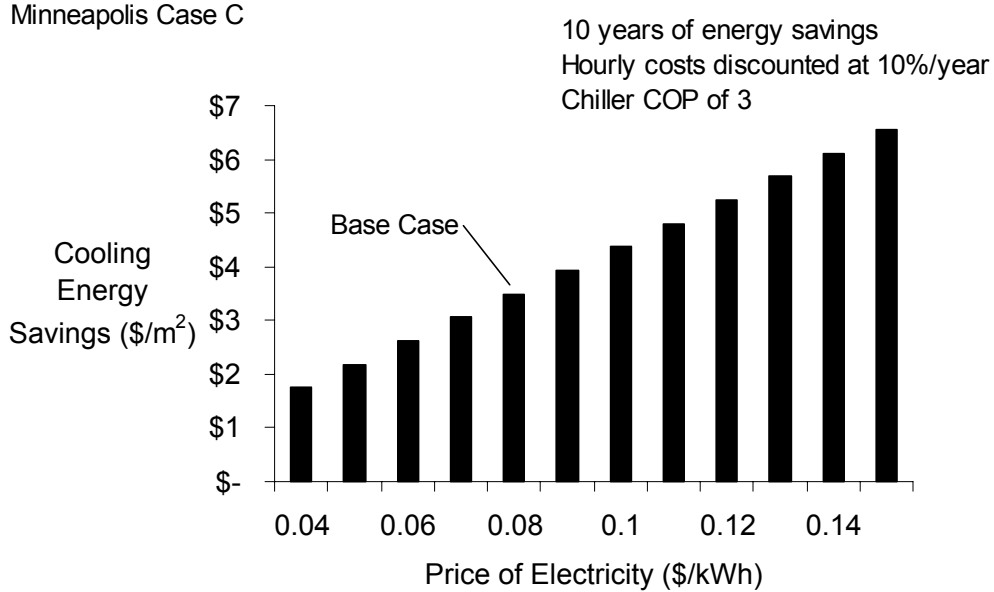


Figure 68. Sensitivity of Minneapolis base case cooling energy cost savings to electricity price.

Consideration of the uncertain spot price of electricity, or rate structures that reflect the general trends of spot prices, would impact the cooling energy savings portion of option value. Spikes in the spot price of electricity are seen in peak hours when demand reaches maximum power generation capacity, and this is positively correlated with outdoor temperature and building loads. One model for simulating spot prices is a switching model, in which an electricity price realization is drawn from one of two probability distributions with “switching” between the distributions (Davison et al., 2002). One of the probability distributions describes non-peak prices and the other probability distribution describes the magnitude of spot prices. The nature of the price of electricity used in the NVOV model is illustrative of an average *non-peak* electricity price seen by the customer (i.e., the building).

Although electricity customers are not generally charged the spot price of electricity directly, the volatility is reflected in the actual rate structures used to bill customers based on the time of day and amount of electricity used. Thus, an understanding of the nature

of spot prices is relevant to exploration of the impact of uncertainty in electricity prices on the NVO option value. The volatility of electricity price depends on the specific market and generation system in which the electricity is consumed and supplied. Figure 69 shows one year of weekday noon electricity prices in the Pennsylvania-New Jersey-Maryland spot market (Davison et al., 2002). Prices spikes of nearly an order of magnitude can be seen in the summer months. In California, made famous in the field of electric power systems due to its energy crisis in 2001, peak electricity prices are as high as \$0.34 per kWh for buildings (including most state buildings) that are on time-of-use rates (Kats et al., 2003). One factor contributing to demand, and thus spot price, is ambient temperature (Valenzuela and Mazumdar, 2001). Increases in ambient temperatures result in increased electricity demand of electric-powered air-conditioning systems. For much of the US, especially in the South and Midwest, air conditioning is the dominant energy user during peak load (Kats et al., 2003). The largest and third largest electricity demands, respectively, in California during a typical 50,000 MW peak load period are commercial air conditioning, representing 15% of peak load, and commercial lighting, representing 11% of peak load (Kats et al., 2003). Clearly, reducing air-conditioning based electricity loads has the potential to play an important role in improving the integrity of large-scale electrical power supply.

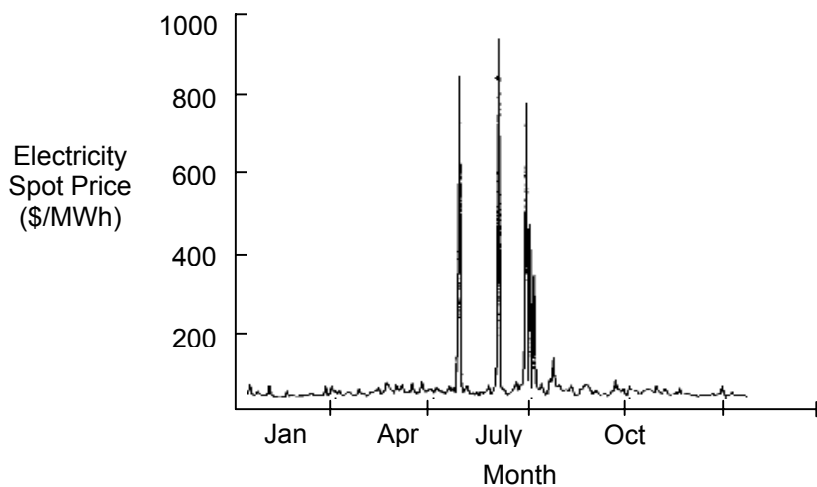


Figure 69. Weekday, noon prices of electricity in the Pennsylvania-New Jersey-Maryland spot market, 1999. Source: Davison et al., 2002.

The following thought experiment shows the range of impact on the cooling energy savings portion of option value when uncertainty in electricity price, via the possibility of price spikes and/or peak demand charges, is considered. The decision rule remains as dependent only on indoor comfort criteria in this discussion. Furthermore, the uncertainty in ambient temperature is already reflected in the building's cooling loads, per the NVOV model. First, if the building's cooling loads can be met by natural ventilation (whether or not the option has already been exercised), then high electricity price realizations will only affect the MC costs. Option value is increased because MC costs are greater. However, if, when high electricity prices are realized, the building must make use of HC to meet cooling loads, then both MC and HC cooling energy costs will be increased by the high electricity prices. Any benefit will arise only if the loads of the HC building are much lower than the MC building. However, if the loads are roughly the same, then no benefit will be seen with the high electricity price. With a sufficient control strategy, the cooling loads of a HC building will not be greater than the loads for a comparable MC building.

If, when the high electricity prices are realized, exercise of the option to install MC is induced for the first time, the impact is ambiguous owing to the simplification made in the model. In reality, a building manager would want to predict the need to install MC before an uncomfortably warm building is experienced, and this is a shortcoming that arises from the necessity of making modeling simplifications. However, even if spikes in electricity costs are caused (in part) by increased ambient temperatures, the option based strategy protects the building from the downside risk of overheating, albeit at the time scale designated in the decision rule if the option has not yet been exercised. Thus, although not exact, it is mostly likely that option value will not be reduced by high electricity price realizations, considering that uncertainty in climate (i.e., the possibility of high ambient temperatures) is already taken into account. Overall, a better understanding of the value of an option based naturally ventilated building, which may turn into a hybrid cooled building, in the face of simultaneous uncertainty in climate and electricity prices warrants further research.

Due to the positive correlation between electricity prices, building cooling loads, and outdoor temperature, there is an impetus to reduce the electricity demand of a building particularly when high realizations of these events occur simultaneously. Building operators will want to reduce electricity requirements so as to reduce their energy bills. At the same time, the utility, or supply side, will want customers to reduce their loads so as to maintain sufficient generation capacity and quality of supply. Demand side management (DSM) is the utility industry term for strategies that encourage customers to reduce their energy demands and/or change the time of usage so that the generator can more efficiently make use of electric generation capacity. From the supply side, high spot electricity prices are the result of nearing the limits of generation capacity. One area of research is to determine how building operators might make use of real-time electricity price information so as to alter their buildings' cooling loads when there is a high market price of electricity (Xing, 2004; Ilic et al., 2002).

Thus far, the formulation of the exercise decision for the option to install MC in the NVO building, as well as the simplified control strategy for turning on mechanical cooling in a HC building, only considered indoor temperature (i.e., comfort) criteria. The uncertain price of electricity did not enter the exercise decision, and it only impacts option value by determining the magnitude of cooling energy cost savings. In other words, the option has not been formulated so as to protect against high realizations of electricity prices explicitly. Implicitly, the owner of an NV building, or any energy conservation building design, is protected against high energy costs due to the energy conservation features of the building. The model's decision rule was formulated with a comfort-based decision rule so as to address the risk of an overheated building, based on the justification that comfort is the underlying determinant of the feasibility of natural ventilation.

To bring the price of energy, via its effect on mechanical cooling costs, into the exercise decision, two advances are needed. First, the building operators and occupants would need to loosen their comfort requirements by accepting and adapting to higher indoor temperature. Brager and de Dear (2000) present research that supports adaptive thermal

comfort standards for naturally ventilated buildings. Adaptive thermal comfort standards would provide building operators with the flexibility to continue operating in NV mode so as to avoid magnified cooling costs induced by a high price of electricity even when indoor temperatures are higher than normally acceptable under MC cooling conditions, such as the decision rule of 29°C used for the results previously presented in this chapter. Second, from a modeling point of view, a model for electricity price correlated with outdoor temperature is needed to simulate the exercise decision. The stochastic model for outdoor temperature developed in this thesis may be used as the building block to which electricity price correlations are added. The electricity price equations may also contain a separate stochastic component, such that a simulated outcome of electricity price depends both on the (random) outdoor temperature and another random variable(s). Appendix I provides a literature review of stochastic pricing models for electric power; however, none consider stochastic ambient temperature in the set of equations that model electricity price.

With this added model component, the NVO exercise decision and the HC operating strategy could be based on acceptable indoor temperature limits as a function of energy costs. When energy costs, or the product of cooling load, equipment COP, and electricity price, reach a certain threshold, a higher threshold of allowable indoor temperature could be allowed so as to reduce or eliminate cooling loads and the associated energy costs. Table 23 gives the 95th and 99th percentiles of indoor temperatures for the base case building in each of the four locations. Although the temperatures for the base case building are high, improved building design might result in lower upper percentiles of indoor temperature. With upper percentiles of indoor temperature within an acceptable range, a table such as Table 23 could be used to guide choice of increased levels of acceptable indoor temperature as a function of energy costs. For example, using the base case building in Seattle, where the simulations conducted in this research already assumed 29°C as the upper threshold on indoor temperature, the fact that 29°C is also the 95th percentile of indoor temperature suggests that a great amount of option value will also be attained by considering uncertainty in electricity prices because the number of events for which the competing decision (i.e., exercise because indoor temperature is too

high) will be small. However, for the other locations, the acceptable indoor temperature will have to be raised to at least 31 or 32°C to reduce the number of occurrences in which the indoor temperature criteria will win over the energy cost criteria in determining exercise, if the base case building design would be used. This is not likely going to be acceptable to occupants, thus pointing to the need to revise the design and reduce the upper percentiles of indoor temperature.

One imaginary limit to this thought experiment is the case in which electricity costs are so high that any indoor temperature is acceptable, as it would be cheaper to send workers home and lose their productive output rather than pay for electricity costs to keep the building comfortable. Estimating that workers' salaries are approximately ten times typical energy costs, that actual productivity is twice the salary, and that the price of electricity is \$0.08/kWh, electricity prices would have to be approximately \$1.60/kWh ($=10 \times 2 \times 0.08$) to justify a scenario in which it is cheaper to send workers home rather than provide comfortable, productive working conditions. (Of course, the workers would probably go home and turn on their air-conditioning, thus negating or reducing any potential benefit to the supply side.) An operating strategy based on both indoor temperature and cooling energy costs would provide the building operator with the compound option of protecting against high indoor temperatures and high electricity prices. Modeling the value of the compound option will have competitive effects since realizations of the two variables are positively correlated but the exercise decisions are opposite. Development of this compound model is an area of future work.

5.11. Discussion on use of results

Real estate developers and building owners can use the results of the options analysis to determine whether or not to invest in a naturally ventilated building with option to install mechanical systems. The results provide information on the amount to invest in design and equipment for the cooling system of the NVO building as compared to a standard mechanically cooled building, for which they likely have data based on past projects. The option value depends on the future exercise cost, and thus there is a tradeoff between

today's costs (for design and equipment) and the future cost of exercise (to install the mechanical cooling system). The two extremes are

- a) zero attention to the flexibility to install in the future, which would represent a large future exercise cost, and
- b) full attention to being able to use mechanical cooling in the future such that the building resembles a hybrid building and almost no exercise costs, nor benefit of delaying, would be incurred to exercise the option.

The range of results helps design teams choose among various features for achieving the flexible building.

The results from the NVOV program help answer the question of what type of cooling system to use – mechanical cooling, hybrid cooling, natural ventilation, or natural ventilation with option - by looking at the relative cooling energy savings, benefit of delayed or avoided capital equipment costs, and frequency distribution of exercise. The results support the role of the designer in addressing and communicating the risk-reward profile of an options-based natural ventilation cooling strategy.

By constructing a NVO building, the owners acquire the right to install a MC system in the future, thereby delaying installation costs. The simulation provides information on the distribution of exercise dates, or how long the MC costs can be avoided. If the option is immediately exercised in the simulation, it is recommended to construct a HC building from the start, and the option value is given by the \$0/m² exercise cost scenario. On the other end of the spectrum, if exercise never occurs in the simulation, then NV alone may be a sufficiently risk-averse choice for the time frame modeled. However, the option may still be valuable due to uncertainty in future use of the building, technical performance, and/or market value of the building with the unfamiliar technology. In between the cases of “no exercise” and “always exercise immediately” lies the cases in which exercise sometimes occurs and/or the year of exercise varies. These cases indicate situations where the option will have the most value for protecting against the risk of an overheated building. Cases that illustrated the value of the option-based strategy are the base case building design in Seattle and San Francisco with a 27°C maximum indoor

temperature, Chicago with a 29°C maximum indoor temperature but 50% glazing, and Minneapolis with a 29°C maximum indoor temperature but 75% glazing or a 5.5 ACH rate of NV airflow.

5.12. Chapter conclusion

Options-based system design is potentially valuable when the primary factors that determine a project's performance are uncertain. For solar and building technologies whose performance is largely determined by evolution of climate, a real options approach to system design may greatly leverage the potential benefits of employing such technologies. The real options framework positions a system to be protected against downside risks while benefiting from favorable outcomes. Real options design is a major departure from static system design and/or static life cycle costing analysis. A better understanding of the means to manage risk through flexible design may help facilitate implementation of innovative technologies.

Development of an option-based strategy for employing natural ventilation under climate uncertainty illustrates the concept. The real options model presented in this section was applied to a building designed for natural ventilation with the option to install a mechanical cooling system in the future in four locations to obtain general guidelines on the applicability of the option-based design. The results demonstrate two advantages of the NVO design as compared to a standard mechanically cooled building: cooling energy savings and shifting of capital cost obligations. Other benefits of the flexible NVO strategy that were not assessed with the model include addressing the risks that the NVO building does not technically perform as expected, cannot meet the cooling and ventilation needs of future uses of the building, and/or that the future selling or rental price of the building is lower than a MC building.

With the flexible design, building owners-investors are positioned to benefit if future climate continues to be suitable for NV. The NVO building resulted in 100 percent cooling energy savings in San Francisco and Seattle over the 10-year analysis, as the option to install MC was never exercised. Furthermore, independent of upside or

downside realization of climate, the NV building with option is superior in terms of cooling energy savings because it defaults to hybrid-cooling if the option is exercised, which consumes less cooling energy than MC. For example, in the Chicago and Minneapolis cases in which the option to install MC was always exercised, and thus the building operated primarily in hybrid-cooling mode, 50-60 percent cooling energy savings were demonstrated compared to MC; fan costs are not included.

The likelihood of exercising the option to install MC is shown to be most sensitive to design parameters, including NV airflow rate and amount of glazing. A small increase in the NV airflow rate and/or a decrease in the amount of glazing, from baselines of 5 ACH and 100 percent glazing respectively, resulted in a lower likelihood of exercise in Chicago and Minneapolis, and thus a much more viable NV building. The impact of increased climate variability on the likelihood of exercising the option depends on the location. In San Francisco and Seattle, increased variability in climate does not reduce the effectiveness of NV, while the opposite is true for the Chicago and Minneapolis base cases. The probability of exercise also depends on the comfort criteria that invoke installation of MC. It is shown that acceptance of higher indoor temperatures will result in successful NV buildings. Thus, the results support adoption of variable comfort standards (i.e., higher acceptable indoor temperatures when high outdoor temperatures are experienced) for NV or hybrid-NV buildings. Although stochastic electricity prices were not considered in this study, future work will demonstrate the greater value that can be realized with a NVO strategy when variable comfort standards are allowed as a tradeoff to high electricity costs.

The methodology of combining a stochastic weather generator with a model of building energy performance is applicable to other building technologies with energy implications. The building energy model can be replaced with a model for the performance of another engineering system dependent on input temperature and solar radiation (using TMY2 data), such as solar photovoltaic arrays. Design firms, manufacturers, and others with a stake in bring emerging technologies to market may apply this methodology to project investment decisions.

6. Discussion and Future Work

The two models for option value developed in this research *separately* covered the issues of market uncertainty and technical uncertainty as motivations for flexible system design. This section begins with a brief review of what the developed models included in their formulation and follows with their limitations or omissions. The latter serve as the starting point for identifying important ongoing and future research needs. Some remarks on future work specific to each study were made in the individual chapters. In this section, future work with more generalized engineering design implications is discussed.

The first model provided a valuation of flexible space design, subject to uncertainty in future rental price of the space (i.e., product value if switched to new use) and timing of the need for the new space-type (i.e., product). Variations of the model considered uncertainty in the amount of space needed for conversion, the possibility of reverting back to the original use, and the optimal decision if a second time-period of conversion is considered at the date when the first decision is made. The model did not consider design details of the systems that would comprise a flexible space, nor other factors in the decision to convert a space. The model only considered the economic value of the option to convert a space to a new use. It did not attempt to quantitatively evaluate other benefits of flexible space design (relative to static design), such as reduced life-cycle materials consumption and improved productivity due to reduced down time when renovation occurs. Important links to explore to achieve greater understanding of the sustainability potential of flexible space design include physical design and integration of systems and components, coordination of financial and technical elements of decision-making, and life-cycle assessment of the environmental benefits.

The second model valued the option to install mechanical cooling (MC) in a naturally ventilated building subject to uncertainty in climate so as to hedge the risk that use of the innovative, sustainable technology might fail. The results provide decision-makers with information on how much to budget for the flexibility to install MC in the future, based on energy and delayed capital costs savings. The model focused on the value of the

option subject to a single uncertainty (i.e., climate). Other relevant uncertainties for which downside realizations may warrant the need to exercise the option to install MC include the market value of the building with NV and/or without MC; change in building use and, thus, loads; and technical failure of the building design and or components to successfully cool the building with NV alone. On the other hand, downside realizations of energy prices, meaning *high* price realizations, might motivate greater acceptance of NV by adapting to higher indoor temperatures and thus less of a need to exercise the option. Consideration of the uncertainty in energy prices makes the option less likely to be exercised while also making the use of NV more valuable. Valuation of the option to install MC subject to multiple uncertainties necessitates development of compound option models in which technical and market uncertainties are considered simultaneously. Only a qualitative description of the NVO design was developed. A better understanding of NVO system components will advance the potential of the options-based strategy by guiding multi-attribute assessment of HVAC equipment choices. Additionally, understanding of the links between design, investment and operating decisions are needed to foster the capacity for implementing flexible design. In the following sections, individual aspects of forward work are briefly discussed relevant to both studies in this research and expanded to engineering system design in general.

6.1.1. Create compound models

When systems are subject to multiple (types of) uncertainties, simulation type real options models and/or combination of real options models with decision tree techniques are required, as discussed in the literature review. When developing such compound models, one important question to address is how the contributions of individual components to option value interact. The correlation of the elemental contributions may result in a fully additive effect on option value. Alternatively, negative correlation may mean that option value arising from one variable's uncertainty is completely canceled out by that of another (uncertain) variable. The NVO study gave examples of each of these. Uncertainties in market value, building loads, and climate have a complimentary effect on option value with no effect on the exercise decision. Uncertainty in electricity prices has a competing effect on the exercise decision, but a complimentary effect on option

value. Another example of compound options lies in maintaining knowledge of the option throughout the project's life. Maintained knowledge of the option is necessary to effectively manage the flexible asset over its lifetime. However, if this knowledge is lost, the option value realization will be zero despite outcomes of uncertain variables for which the option provided the most value. This is an important area of forward work, particularly for its relevance to practical implementation of flexible design strategies. Furthermore, comprehensive inclusion of relevant uncertain variables in the modeling activities will provide a greater depth of information for decision-makers.

6.1.2. Explore design issues

To develop more comprehensive real options valuation models and to help facilitate transfer of “design for flexibility” concepts to practice, development of design schematics and guidelines are needed. To aid the effort of designers, development of design guidelines for flexibility based on the types and magnitudes of uncertainty for general classes of systems, such as the use of a space and HVAC systems, is one area of forward work. The word “systems” is particularly relevant in this context. In high-performance designs, systems are highly integrated and choices related to individual goals will thus impact system performance with respect to other goals. For example, design of a flexible office space may include underfloor air distribution systems, which also conserve energy as compared to overhead, forced air systems. Schematic or conceptual designs will greatly aid assessment of the compound option value of a flexible system. Furthermore, preliminary designs are needed to (begin to) assess cost estimates and lifecycle impacts of materials and other design choices. Thus, an important area of forward work is to assemble an interdisciplinary team of engineers, architects, and real-options analysts to provide more detail and rigor to the definition of flexible design and its value.

Additionally, development of flexible design typologies will help facilitate real-world implementation of flexible strategies by providing a starting point for designers to use in their own designs. Use of options-based design to provide a fallback position when innovative technologies are employed, as in the NVO case, is one promising area for forward work. Other sustainable, innovative technologies whose risks, and opportunities,

may be addressed with options-based design, and thus represent forward work, include daylighting, renewable energy installations, and interactions of elements within highly integrated building designs. Flexible design typologies would play an educational role for stakeholders by providing physical form to the concept. Research is needed to understand other barriers, not related to education or creative design capacity, that inhibit flexible design, including integration into traditional design processes with their entire casts of contributors, contractual or liability arrangements, and management methods, including transfer of design to those responsible for operational decisions. Future research towards the goal of building the capacity to increase the rate of implementation of innovative, environmentally beneficial technologies is needed in the areas of contractual formats among parties, better understanding of how the real options approach to design will be undertaken in practice (i.e., in design charrettes and decision-making meetings), and understanding of how liability might propagate throughout the various interested parties with an options approach to system design.

6.1.3. Data on cost estimates and conversions

Public access to cost data and records of physical exercise of options will greatly increase the understanding of options based design and its role in improving the economic and environmental qualities of a project. The framework developed in this research provides a basis for collecting such information, and this area of work is the empirical portion missing from the current research study. Because, in the buildings and construction industry, cost data is generally kept private due to high levels of competition, formation of a consortium in which cost data would be shared is one way forward for developing databases that support development of real options models. The “Agile Workplace” consortium lead by Michael Bell and Michael Joroff (2001) was founded with the mission to study the organizations that design and maintain the places and systems that enable work. Industry sponsors included information technology companies and the corporate real estate departments of major corporations. The concept of an “evolving workplace” was addressed, and addition of the mission to consider cost and environmental factors of flexible design would be logical inclusions to the research mission.

Overall, identification of data needs represents an important, albeit general, finding from this dissertation - improving the policy relevance of real options modeling requires more detailed data. Databases of market variables, equipment costs, and more are needed to aid construction of real options models. Example data needs identified in the flexible-space options model include market value of non-office space types, market value differentiation of flexible and inflexible space, records of investment in flexibility and subsequent exercise, and other costs associated with exercise. Databases and information clearing houses are already used by the EPA and state agencies to disseminate best-practice environmental information. Thus, coordination of publicly accessible flexibility databases (with information on costs, design typologies, etc.) is a clear need first for the initiation of flexibility conversations within design teams and later for widespread dissemination as learning occurs.

6.1.4. Assess sustainability impacts with life cycle analysis

The final area of forward work is one of the most important in terms of understanding the potential of flexible design strategies to meet environmental goals. The flexible design may originate from goals to minimize waste or reduce the risk of using a new, promising technology. Sustainability goals include costs, environment, and impact on users (which may include society as a whole). Whereas the real options models developed in this research primarily addressed the issues of cost, with the goal of demonstrating the financial soundness of flexible design, a full understanding of the sustainability attributes of flexible design requires research in the areas of environmental and user impacts. The NVO study reached slightly into this field by considering the energy savings in terms of kWh of the flexible strategy. These results could be further translated to emissions savings using the characteristics of an assumed energy (electricity) source as relevant to the location and/or individual project. Policy makers in particular are concerned with goals of environmental impact, along with, of course, the economic cost/benefit of candidate technologies. Energy is a primary topic in policy circles.

The push from the environmental or sustainability community is to consider a product's environmental impact from cradle to grave, taking into account air emissions, material waste, toxic chemicals, and energy use over the entire life time of the product. An example of cradle-to-grave practice in the buildings industry is that the LEED guidelines acknowledge impacts ranging from initial materials choice to reusability of components at the end of a building's life. LCA evaluations provide comprehensive assessment of a design's environmental performance, and can be used to compare design alternatives. However, they are a challenging undertaking, particularly for complex designs, because of needs to define system boundaries and obtain data for many input variables. Use of LCA in a real options framework increases the complexity level a notch by adding in uncertainty in the service or use phase of the product. The possibility for the product to take different paths of evolution during its lifetime requires a probabilistic description of its impacts in the possible states that it could exist. Extraction of the probabilistic states and/or parallel development of real options and LCA data for a particular project are necessary, and represent a broad new area of research.

7. Conclusion

Real options methodologies, like decision analysis, embrace uncertainty as a guide for structuring decisions over time. In the architectural and engineering design processes, uncertainty is usually addressed by designing for worst-case scenarios so as to achieve a robust design. However, design for the worst-case scenario may result in an overly conservative design that costs more than is otherwise necessary. At the same time, the design alternatives that considered the upside potential of the uncertain variables may have been discarded in favor of providing a robust, failure-proof design. The over-sizing of mechanical cooling systems in commercial buildings and mindset that passive cooling approaches will not meet (hot and humid) design-day conditions are examples of this conservative design approach. To change the traditionally conservative way in which buildings are designed and built, new means of addressing the risks imposed by uncertainty in future performance are needed.

This research developed a flexible, options-based approach for addressing uncertainty of the future performance of a system through design. A flexible design is defined as one that includes one or more option(s), or the right, but not the obligation, to take an action in the future. The premise advanced in this research, through development of real options valuation models, is that a flexible design strategy that addresses uncertainties can hedge losses and also provide opportunities, thereby resulting in an improved investment as compared to a static design. The research is largely motivated by the need to achieve widespread practice of sustainable building design. The hypothesis is that flexible-design supported by a real options valuation methodology provides valuable insights to decision-makers concerned about the uncertainties, and thus risk, associated with sustainable building designs and technologies.

Two cases of flexible design relevant to sustainable buildings demonstrated how both the benefits and risks arising from uncertainties can be addressed. The first case, ‘flexibility in space-use,’ provides investment guidance on designs that seek to enhance the longevity of a building by facilitating change to new uses. The second case, ‘flexibility as

an implementation strategy for NV,' provides a tool for understanding the impact of climate uncertainty on the future performance of a naturally ventilated building. Both cases are examples of economic valuation under uncertainty. Unlike typical valuation approaches, such as net present value or life cycle costing methodologies that use expected values of a system's performance under average conditions, the real options method incorporates uncertainty over time and explicitly depends on the ability to make decisions in the future. The real options methodology addresses both the design and investment decision-making communities so as to provide them with information on how flexible design addresses perceived risks while also positioning the project to take advantage of upside opportunities.

To further advance the potential of flexible design, this research also developed models to support the decision-making process. A real options model provides information to decision-makers as to the value of a flexible approach to a problem under question, such as a staged investment decision or a flexible technical system. Most real options models in the literature are based on financial-options theory and are concerned with determining a single value, or "price" of the flexibility. However, decisions pertaining to flexible design of complex, non-linear systems under uncertainty, such as buildings, do not generally fit the assumptions and solutions for financial-options methodologies. Simulation is another class of real options methodologies, which as opposed to financial-options methodologies allow any choice or manner of describing the behavior of uncertain variables. Two models were developed in this research: one that combined financial and simulation methodologies and one that used a parametric-model based on physical principals of how the non-linear system performs in an uncertain operating environment.

The first model determined the value of flexible designs that facilitate change of space-use. Whereas flexible design, for the purpose of increasing building longevity, is a sustainable building guideline, this study aimed to provide guidance to decision-makers regarding how much to spend on such flexibility. Building owners and property developers can use the option value results to decide how much to invest in the design

and construction features necessary to gain a flexible space. Thus, the model provides decision-making support for situations in which flexibility intuitively makes sense, such as the case study of the laboratory building with option to convert to office space.

The model for flexibility in space-use combined financial and simulation real options principles. A binomial lattice was used to model uncertainty in rental price and to value the option, and Monte Carlo simulation was used to model uncertainty in timing and other uncertain variables, such as the amount of space needed. The fundamental financial assumptions limit application of the model to conversions to space types for which complete markets exist, such as office space in dynamic urban or suburban markets. The inputs used for the case study were developed for a corporate campus located in a suburban area that had a dynamic office space market; thus use of the financial model was justified. However, based on highest and best use principles, it is reasoned that the financial model can be used as a guideline for investing in the flexibility to change to any type of space.

The base case flexibility in space-use model showed that, as with a standard call option on a stock, the option value to renovate for a prespecified renovation cost increases with a longer time horizon and decreases with increased renovation cost. It is shown that the option value is more sensitive to time horizon, or future exercise date, as the renovation cost increases. The value of the flexibility to renovate is also sensitive to the parameters of the lease (i.e., opportunity cost of capital and the duration of the lease), but it is not sensitive to a two-percent annual rate of inflation in renovation costs. It is shown that even inflexibly designed spaces, or ones that cost \$500/SF to renovate to office space, have some inherent option value, which can be physically explained by the basic need of a structure and building shell to support any space-type.

Inclusion of uncertainty in the amount of space needed at the future date allows for consideration of parsing the space into various levels of flexibility. It is shown that the total option value increases as the amount of flexible space increases; however normalizing option value to the amount of flexible space does not produce a monotonic

trend as a function of the inflexible, or less flexible, renovation cost. A case is also presented for the option to revert back to the original space type by paying a second renovation cost. To preserve the validity of the financial options model, the reversion scenario is compared to a scenario in which office space is simply rented for the interim period, thereby leaving the original space-type intact for the subsequent time period. It is shown that, due to greater renovation costs (i.e., the sum of costs to convert to office space and to convert back to the original space type), the option value is less than the base case model. A compound model, in which the decision to rent or renovate also depends on the value of leaving the option open for renovation in a second time period, indicates that decision-making based on comparison of the instantaneous rental price and renovation cost is sufficient; extra analysis to determine the “open” option value is not necessary. In general, it is shown that, for the flexibility to convert a space to another use, parameters such as time horizon, uncertainty in rental value, and fraction of the space that is made to be flexible increase option value. On the other hand, increased renovation costs decrease the value of flexibility. These general principles can be applied to any case for flexibility in space-use.

Furthermore, the Black-Scholes formula, when evaluated with the maximum time horizon for the date of space need, can be used to determine the upper limit on the value of a design that can be renovated to office space. Also, if it is assumed that 100 percent of the space will be needed on the exercise date, the expected value of the exercise date can be used in the Black-Scholes formula to approximate option value, for the probability distributions assumed in this research. These findings indicate a useful, quick approximation for guiding investment in flexible designs that accommodate future changes in space-use.

This second model developed in this research, the Natural Ventilation Option Valuator (NVOV), represents a new concept for application of real options theory: to support implementation of innovative, risky, yet beneficial technologies through flexible design. The innovative technology studied is natural ventilation, which is a passive cooling strategy that may be an effective alternative to mechanical cooling in temperate climates.

The benefits of natural ventilation include improved indoor environmental quality, and thus improved occupant satisfaction and/or improved productivity; reduced cooling energy consumption, and thus reduced operating costs which are particularly valuable given rising energy prices; and reduced capital equipment needs, and thus reduced first costs. However, building owners, developers, and designers are reluctant to adopt the technology partially due to the risk that the building might become overheated, partly as a result of uncertainty in future climate. Additionally, they are inhibited by the risk that the market will not accept a naturally ventilated building due to perceived comfort risks.

The real-options insight is that, for a location where initial feasibility studies of the building and climate suggest that NV is suitable for cooling, the building could be designed for NV along with the option to install MC in the future. The decision rule for exercising the option in the NVOV model is based on comfort criteria. Thus, the option-based building is positioned to take advantage of energy savings and delayed capital cost savings potential, and it is positioned to be protected against downside losses when unfavorable outcomes arise, such as a warm summer. An average price of electricity is used to calculate energy savings. Uncertainty in electricity prices is not considered, other than in sensitivity analysis, because the exercise decision is based on comfort criteria, not on instantaneous cooling costs. However, it is reasoned that electricity ‘price-spikes’ would have the effect of increasing option value. The model helps designers test sensitivity of design parameters and communicate the potential of the option-based naturally ventilated building subject to uncertainty in future daily outdoor temperature. Decision-makers can use the likelihood of exercise and the cost savings from energy and delayed or avoided capital costs to decide whether or not to invest in the option-based strategy.

The model to evaluate the NVO strategy departs from much of the real-options literature. It is based on simulation modeling concepts for real options, but differs in that it requires a model of the physical performance of the system to determine the exercise date (i.e., the date at which comfort criteria are exceeded) and part of the option-value (i.e., the cooling loads of the comparison MC building). Inclusion of a model for the physical

performance of a system departs from most real options models, which are typically based on cost models and/or idealized equations for the economic performance of a system with technical parameters. The source of uncertainty in the NVOV model is variability in outdoor temperature, which is modeled by applying Gaussian noise to a weather (i.e., TMY2) data set. The stochastic climate module of the model is applicable to real options models for other engineering systems that depend on climate as a major determinant of their success or failure, such as solar photovoltaics.

A baseline NV building design with the option to install MC (i.e., the NVO building) was tested in four locations with the NVOV model: Seattle, San Francisco, Chicago, and Minneapolis. In 100, 10-year trials in San Francisco and Seattle, the NVO building resulted in 100 percent cooling energy savings, as the option to install MC was never exercised. Conversely, in Chicago and Minneapolis under the same comfort criteria and building design assumptions, it was shown that hybrid cooling is necessary from the start. However, by slightly increasing the allowable hours at or above the assumed maximum temperature of 29°C, reducing the amount of glazing, and/or increasing the NV airflow rate, the feasibility of a NVO strategy was greatly improved. Because capital costs for cooling equipment, such as chillers and cooling towers, are much greater than the present value of typical cooling energy costs over a ten-year period (i.e., approximately double, or more), the benefit of delaying or avoiding capital costs is shown to be of greater significance than cooling energy cost savings. This finding supports consideration of NVO cooling strategies as opposed to hybrid MC-NV strategies that require capital cooling equipment at the beginning.

Overall, the likelihood of exercising the option to install MC, thereby mitigating the risk that the building overheats, is shown to be most sensitive to design parameters and comfort criteria as opposed to variability in climate. The impact of increased climate variability on the likelihood of exercising the option depends on the location. In San Francisco and Seattle, increased variability in climate did not reduce the effectiveness of NV, while the opposite was true for the Chicago and Minneapolis base cases. The probability of exercise also depends on the comfort criteria that invoke installation of

MC. It is shown that acceptance of higher indoor temperatures will result in successful NV buildings. Thus, the results support adoption of variable comfort standards (i.e., higher acceptable indoor temperatures when high outdoor temperatures are experienced) for NV or hybrid-cooled buildings. Although stochastic electricity prices were not considered in this study, future work will demonstrate the greater value that can be realized with a NVO strategy when variable comfort standards are allowed as a tradeoff to high electricity costs. Furthermore, future work will look at implementation guidelines and monitoring strategies for managing the flexibility of a NVO building.

The research focused on a real options design methodology to be integrated into current design processes. In practice, it is pertinent that flexible design be considered at the earliest stages of the design process. For flexibility to be valuable it must actually be managed over the project's operational lifetime; thus early buy-in from owners and/or developers is essential. The research also focused on modeling of option value, and thus necessitated simplified decision rules for enacting, or exercising elements of flexibility. Application of options-based design in practice will require further consideration of executable decision-making strategies and methodologies for monitoring uncertain events. Other future areas of work to advance the flexible design concept include developing schematic designs for flexible spaces and option-based natural ventilation cooling systems, as well as assessing the sustainability impact of flexible design with life cycle analysis of mass and emissions flows. Furthermore, the concepts may be extended to address the risks of other innovative technologies, including daylighting strategies, renewable energy integration into buildings and grid systems, and transportation systems. Flexible design holds potential to advance the cause of sustainability, and the conclusions of this research suggest a way forward for improved understanding of the relationship between flexibility and sustainability.

8. References

- Allard L and Barber C. 2003. Challenges and Opportunities in Aligning Real Estate and the Workplace with Business Strategy: A survey of leading CEOs. *Journal of Corporate Real Estate*. Vol. 5 No. 3. pp. 213-220.
- Alvarado FL and Rajaraman R. 2000. Understanding price volatility in electricity markets. IEEE. Proceedings of the 33rd Hawaii International Conference on System Sciences. pp.1-5.
- Amram M and Kulatilaka N. 1999. *Real Options: Managing strategic investment in an uncertain world*. Chapters 1, 2. Harvard Business School Press. Boston, MA.
- Arons D. 2000. Properties and Applications of Double-Skin Building Facades. Master of Science Thesis. Massachusetts Institute of Technology, Department of Architecture. Cambridge, Massachusetts.
- Ashford NA. 2002. Incorporating Science, Technology, Fairness, and Accountability in Environmental, Health, and Safety Decisions. Adapted from “Implementing a Precautionary Approach in Decisions Affecting Health, Safety, and the Environment: Risk, Technology Alternatives, and Tradeoff Analysis” in *The Role of Precaution in Chemicals Policy*, Favorita Papers 01/2002, E Freytag, T Jakl, G Loibl, M Wittmann (eds.), Diplomatic Academy, Vienna, pp 128-140.
- Avis M. 1990. in Gibler K, Black RT, and Moon KP. 2002. Time, Place, Space, Technology and Corporate Real Estate Strategy. *Journal of Real Estate Research*. No. 3. pp. 235-262.
- Baldwin CY and Clark KB. 2001. *Design Rules: The power of modularity*. Volume 1. MIT Press. Cambridge, Massachusetts.
- Barrow E and Lee R. 2000. ‘Appendix E. Stochastic Weather Generators.’ in *Climate Change and Environmental Assessment. Part 2: Climate Change Guidance for Environmental Assessments*. Prepared for the Research and Development Monograph Series, 2000. The Canadian Institute for Climate Studies.
http://www.ceaa-acee.gc.ca/015/0002/0004/print-version_e.htm Cited January 17, 2005.
- Batchelor, James P, AIA. Principal, Arrowstreet Inc. Personal communication with. April 30, 2003.
- Bell M and Joroff M (Co-Project Directors). 2001. *The Agile Workplace: Supporting people and their work*. A Research Partnership between Gartner, MIT, and 22 Industry Sponsors. Gartner and Massachusetts Institute of Technology. Cambridge, Massachusetts. December 2001.

Black F and Scholes M. 1973. The Pricing of Options and Corporate Liabilities. *Journal of Political Economy*. Vol. 81. No. 3. pp. 637-654.

Bordass B, Cohen R, Standeven M, and Leaman A. 2001. Assessing Building Performance in Use 2: Technical performance of the Probe buildings. *Building Research & Information*. Vol. 29, No. 2. pp. 103-113.

Borison A. 2003. Real Options Analysis: Where are the Emperor's Clothes?. *Real Options Conference 2003*. Washington, D.D. July 2003. <http://www.realoptions.org/abstracts/abstracts03.html>.

Bottom CW, McGreal WS, and Heaney G. 1999. Appraising the functional performance characteristics of office buildings. *Journal of Property Research*. 16(4). P. 339-358.

Brager GS and de Dear R. 2000. A Standard for Natural Ventilation. *ASHRAE Journal*. October 2000. Vol. 42, No. 10, p. 21-28.

Brand S. 1994. *How Buildings Learn: What happens after they're built*. Penguin Books USA Inc. New York, New York.

Brealey RA and Myers SC. 2000. *Principles of Corporate Finance*. Sixth Edition. McGraw-Hill. Boston, Massachusetts.

Byrne P. 1996. *Risk, Uncertainty and Decision-Making in Property Development*. Second Edition. 'Chapter 1: Uncertainty, risk and the process of property development.' E and FN SPON. London, UK.

CB Richard Ellis, Inc. 2003. *Suburban Office Market Index Brief – Chicago Q2 2003*.

Childs PD, Riddiough TJ, and Triantis AJ. 1996. Mixed Uses and the Redevelopment Option. *Real Estate Economics*. Vol. 24, No 3. pp.317-339.

City Guide for Istanbul.

<http://www.istanbul.com/ExploreDetail.asp?CatID=7#here?CatID=7>. Cited December 5, 2002.

Cooke RM. 1991. *Experts in Uncertainty: Opinion and subjective probability in science*. Oxford University Press. New York, New York.

Copeland T and Antikarov V. 2001. *Real Options: A practitioner's guide*. Ch. 5-10. Texere Publishing Limited. New York, NY.

Cox JC, Ross SA, and Rubinstein M. 1979. Option Pricing: A Simplified Approach. *Journal of Financial Economics*. Vol. 7. pp. 229-263.

Cushman & Wakefield, Inc. 2003. *Chicago, IL Office Market – Second Quarter 2003*.

Diamond RC. 2001. An Overview of the U.S. Building Stock. Chapter 2.1 in *Indoor Air Quality Handbook*, Spengler J.D. et al. McGraw Hill. New York, New York.

Davis A. 2001. Barriers to Building Green. *Architecture Week*. http://www.architectureweek.com/2001/0822/environment_1-1.html. [cited 15 February 2005].

Davison M, Anderson CL, Marcus B, and Anderson K. 2002. Development of a hybrid model for electrical power spot prices. *IEEE Transactions on Power Systems*. Vol. 17, No. 2. pp 257-264.

Dean BN. 2001. Natural Ventilation Possibilities for Buildings in the United States. Master of Science Degree Thesis. Building Technology Program, Department of Architecture. Massachusetts Institute of Technology. Cambridge, MA.

de Gids WF. 1998. Barriers to Natural Ventilation Design of Office Buildings. National Report: The Netherlands. <http://projects.bre.co.uk/natvent/reports/barrier/nlbar.pdf>. Cited February 27, 2004.

de Neufville R, Scholtes S, and Wang T. 2005. Valuing Real Options by Spreadsheet: Parking Garage Case Example. *Journal of Infrastructure Systems*. American Society of Civil Engineers (ASCE). Forthcoming.

de Neufville R. 1990. *Applied Systems Analysis: Engineering planning and technology management*. McGraw-Hill Inc. New York, New York.

de Weck O, de Neufville R, and Chaize M. 2003. Enhancing the Economics of Communication Satellites via Orbital Reconfigurations and Staged Deployment. *Space 2003 Conference*. Long Beach, CA. Sept. 23-25, 2003. AIAA Paper 2003-6317.

De Wit S and Augenbroe G. 2002. Analysis of uncertainty in building design evaluations and its implications. *Energy and Buildings*. Vol. 34. pp. 951-958.

Diamond RC. 2001. An Overview of the U.S. Building Stock. Chapter 2.1 in *Indoor Air Quality Handbook*, Spengler J.D. et al. McGraw Hill. New York, New York.

Dixit AK and Pindyck RS. 1994. *Investment Under Uncertainty*. Ch. 3 "Stochastic Processes and Ito's Lemma." pp. 59-92. Princeton University Press. Princeton, New Jersey.

DOE (U.S. Department of Energy). 2000. High Performance Commercial Buildings: A Technology Roadmap. October 2000. Office of Building Technology, State and Community Programs. Washington, D.C. http://www.eere.energy.gov/buildings/info/documents/pdfs/roadmap_lowres.pdf. Cited 15 February 2005.

Donovan RJ. 2001. Green Building Technologies: Should a Developer Implement Photovoltaics, Underfloor Air Distribution, and Natural Ventilation?. Master of Science Thesis. Massachusetts Institute of Technology. Cambridge, Massachusetts.

Dunbar N. 2000. *Inventing money: The story of Long-term Capital Management and the legends behind it*. Wiley Inc. New York, New York.

EIA (U.S. Energy Information Administration). 2003. <http://www.eia.doe.gov/>.

Energy Star. 2005. Homebuyer Incentives. http://www.energystar.gov/index.cfm?c=new_homes_benefits.hm_b_financial_incentives. Cited March 15, 2005.

ESM (Engineered Systems Magazine). 2003. Case in Point: Hybrid electric/steam chiller plant gives Terps home court advantage. Posted on 09/26/2003. http://www.esmagazine.com/CDA/ArticleInformation/Case_Item/0,2534,108483,00.htm. Cited 15 February 2005.

Fawcett W. Personal communication with. December 16, 2002.

FCC (Federal Facilities Council). 1996. Federal Policies to Foster Innovation and Improvement in Constructed Facilities: Summary of a Symposium. Federal 'Barriers to Change.' pp. 17-44. <http://www.nap.edu/books/NI000086/html/index.html> Accessed February 26, 2004.

Fernandez JE. 2002. Diversified Longevity: Orchestrated obsolescence for intelligent change. *Thresholds 24: Reproduction and Production*. Massachusetts Institute of Technology. Cambridge, Massachusetts. Spring 2002. pp. 13-19.

Fisk WJ. 2000. Health And Productivity Gains From Better Indoor Environments and Their Relationship With Building Energy Efficiency. *Annual Review of Energy and the Environment*. 25:537-66.

Friedman A. 1993. 'A Decision-Making Process for Choice of a Flexible Internal Partition Option in Multi-Unit Housing Using Decision-Theory Techniques.' In *Design and Decision Support Systems in Architecture*, Timmermans H, ed. pp.179-188. Kluwer Academic Publishers. The Netherlands.

Geltner D. 1989. On the Use of the Financial Option Price Model to Value and Explain Vacant Urban Land. *AREUEA Journal*. Vol 17. No 2. pp. 142-158.

Geltner DM and Miller NG. 2001. *Commercial Real Estate Analysis and Investments*. South-Western Publishing. Mason, Ohio.

Geltner D, Riddiough TJ, and Stojanovic S. 1996. Insights on the Effect of Land Use Choice: The perpetual option on the best of two underlying assets. *Journal of Urban Economics*. Vol 39. pp. 20-50.

Gladstone J. 1998. John Gorrie, The Visionary: The First Century of Air Conditioning, Article 1. *ASHRAE Journal*. December 1998. pp. 29-35.

Greden LV. 2001. The Demand Side of China's Evolving Housing Market and Sustainability: Stakeholder analysis and policy approaches. Master of Science Degree Thesis. Technology and Policy Program. Massachusetts Institute of Technology. Cambridge, MA.

GBCA (Green Buildings Council Australia). 2004. Changing Offices, Challenging Churn. June 10, 2004. <http://www.gbcaus.org/gbc.asp?sectionid=6&docid=464>.

Hokoi S and Matsumoto M. 1993. An Analysis of Stochastic Properties of Room Temperature, Cooling Load and Air-conditioning Systems. *Building and Environment*. Vol. 28 No. 4. pp. 497-508.

Huang, Jeff. Mechanical Engineer, Arup, Inc. Personal communication with. March 17, 2005.

Ilic M, Black JW, and Watz JL. 2002. Potential Benefits of Implementing Load Control. *Proceedings IEEE Power Engineering Society Winter Meeting*. January 2002. New York, NY. Vol. 1. pp. 177 –182.

Jeans, Sir James. 1959. *An Introduction to the Kinetic Theory of Gases*. The Cambridge University Press. Cambridge, UK. p. 218-224.

Jennergren LP and Naslund B. 1996. A class of options with stochastic lives and an extension of the Black-Scholes formula. *European Journal of Operational Research*. 91 pp. 229-234.

Jiang Y and Hong T. 1993. Stochastic Analysis of Building Thermal Processes. *Building and Environment*. Vol. 28, No. 4. pp. 509-518.

Johnson, T. 2005. Course notes for “15.437, Options and Futures Markets.” Massachusetts Institute of Technology. Sloan School of Management. Autumn 2004.

Joroff M and Bell M, eds. 2001. *The Agile Workplace: Supporting People and Their Work*. December 2001. Gartner and Massachusetts Institute of Technology. Cambridge, Massachusetts.

Kalligeros K. 2003. Framework for the Optimal Design of Corporate Facilities for Contracting Operations. *The Sixth SMESME International Conference*. 1-4 June 2003. Athens, Greece.

Kats G, Alevantis L, Berman A, Mills E, and Perlman J. 2003. *The Costs and Financial Benefits of Green Buildings: A Report to California's Sustainable Building Task Force*. October 2003. <http://www.usgbc.org/Docs/News/News477.pdf>. Cited 21 January 2005.

Kiraly A and Janosi IM. 2002. Stochastic Modeling of Daily Temperature Fluctuations. *Physical Review E*. Vol 65. pp. 051102-1 - 051102-6.

Kulatilaka N. 1993. The Value of Flexibility: The Case of a Dual-Fuel Industrial Steam Boiler. *Financial Management*. Autumn 1993. pp.271-280.

Leaman A and Bordass B. PROBE 15 Productivity: The killer variables. 1998. *Building Services Journal*. June 1998. pp.E19-21.

Lehar MA and Glicksman LR. 2004. A Simulation Tool for the Optimization of Advanced Facades. *SimBuild 2004*. Boulder, CO. August 4-6, 2004.

Levermore CD, Jones P, and Lister D. 2004. Accuracy of modelled extremes of temperature and climate change and its implications for the built environment in the UK. Tyndall Centre for Climate Change Research. Technical Report 14. April 2004. http://www.tyndall.ac.uk/research/theme3/final_reports/it1_8.pdf. Cited October 19, 2004.

Loftness V and Mathews P. 1999. Sustainable Development Alternatives for Speculative Office Buildings. Center for Building Performance and Diagnostics, Carnegie Mellon University. Pittsburgh, PA. 26 May 1999.

Loftness V, ed. 2001. Building Investment Decision Support (BIDS): Cost-Benefit Tool to Promote High Performance Components, Flexible Infrastructures, and Systems Integration for Sustainable Buildings and Productive Organizations. ABSIC Research 2000-2001 Final Report. pp. 1-22. http://www.eere.energy.gov/femp/aboutfemp/pdfs/nov01_femac_loftness.pdf. Cited January 15, 2004.

Loftness V. 2004. Improving Building Energy Efficiency in the U.S.: Technologies and Policies for 2010 to 2050. Prepared for the PEW Center on Global Climate Change. May 2004. p.1-12. <http://www.house.gov/science/hearings/energy04/may19/loftness.pdf>. Cited 21 January 2005.

Longstaff F and Schwartz ES. 2001. Valuing American Options by Simulation: A simple least-squares approach. *The Review of Financial Studies*. Vol 14, No 1. pp.113-147.

Mallozzi J. 2003. A Vertical Solution in an Urban Setting. Reed Business Information. Morris Plains, NJ. May 2003. <http://www.elkus-manfredi.com/RDloy.pdf/>.

McDonald RL. 2003. *Derivatives Markets*. Pearson Education, Inc. Boston, Massachusetts.

McDonough W and Braungart M. 2002. *Cradle-to-Cradle: remaking the way we make things*. North Point Press. New York, New York.

Mendler S and Odell W. 2000. *The HOK Guidebook to Sustainable Design*. John Wiley & Sons, Inc. New York, New York.

Merton RC. 1973. Theory of Rational Option Pricing. *Bell Journal of Economics and Management Science*. Vol. 29. pp. 141-183.

Miller B and Clarke JP. 2004. Application of Real Options to Evaluate the Development Process of New Aircraft Models. AIAA 4th Aviation Technology, Integration and Operations (ATIO) Forum. 20-22 September 2004. Chicago, Illinois. AIAA 2004-6498. pp. 1-11.

MIT Design Advisor (Version 1.0). <http://designadvisor.mit.edu/design/>. Cited March 14, 2005.

MSBG (Minnesota Sustainable Building Guidelines). 2003. Center for Sustainable Building Research, College of Architecture and Landscape Architecture, University of Minnesota. http://www.csbr.umn.edu/b3/MSBG_v1_1.pdf. Cited January 1, 2005.

Moel A and Tufano P. 2000. "Bidding for the Antamina Mine – Valuation and Incentives in a Real Option Context" in *Project Flexibility, Agency, and Competition*. Edited by Brennan M and Trigeorgis L. Oxford University Press.

Moreno M. 2000. Riding the Temp. *Future and Options World*. pp.1-12. <http://www.weatherderivs.com/Papers/Riding.pdf>. Cited July 8, 2004.

Neely JE and de Neufville R. 2001. Hybrid Real Options Valuation of Risky Product Development Projects. *International Journal of Technology, Policy and Management*. Vol. 1, No.1. pp. 29-46.

NIST Building Life-Cycle Cost Program. http://www.eere.energy.gov/femp/information/download_blcc.cfm#blcc5. Cited March 14, 2005.

NREL (National Renewable Energy Laboratory). User's Manual for TMY2s. <http://rredc.nrel.gov/solar/pubs/tmy2/overview.html#descrip>. Cited March 15, 2005.

OTA (Office of Technology Assessment), U.S. Congress. 1992. *Building Energy Efficiency*. (OTA-E-518). Washington, D.C: U.S. Government Printing Office.

Pace C. and Gilda G. 1998. Cost and Risk Analyses in Building Systems. *Congress on Commuting in Civil Engineering*. pp.235-246.

Patel K. and Paxson D. 2001. Real urban development options at Canary Wharf. Ch. 9 in *Real Options: Evaluating corporate investment opportunities in a dynamic world*. Financial Times/Prentice Hall. London, UK. pp. 163-176.

PIER. 2003. Energy Efficient and Affordable Small Commercial and Residential Buildings Research Program. Alternative Cooling. <http://www.archenergy.com/cec-eeb/P4-AdvCooling/index.htm>. Cited February 27, 2004.

Pindyck RS. 1999. Irreversibilities and the Timing of Environmental Policy. pp. 1-31. <http://web.mit.edu/rpindyck/www/envtime.pdf>. Cited March 18, 2003.

Prins M, Bax MFTH, Carp JC, Tempelmans Plat H. 1993. 'A Design Decision Support System for Building Flexibility and Costs.' In *Design and Decision Support Systems in Architecture*, Timmermans H, ed. pp.147-163. Kluwer Academic Publishers. The Netherlands.

Raftery J. 1991. *Principles of building economics: An introduction*. Blackwell Science Inc. Oxford, UK.

Raue AK, Luscuere PG, and Boerstra AC. 2002. Natural Ventilation In Office Buildings - The Do's And Don'ts. *Proceedings: Indoor Air 2002*. pp. 842-47.

RS Means. 2005. *Building Construction Cost Data. 63rd Annual Edition*. Reed Construction Data, Inc. pp. 511.

Semenov MA and Barrow EM. 1997. Use of a Stochastic Weather Generator in the Development of Climate Change Scenarios. *Climatic Change*. Vol. 35. Issue 4. pp. 397-414.

Sensharma NP, Woods JE, and Goodwin AK. 1998. Relationships Between the Indoor Environment and Productivity: A Literature Review. *ASHRAE Transactions: Research*. 4164 (RP-700). pp. 686-701.

Skantze P. 2001. A Fundamental Approach to Valuation, Hedging, and Speculation in Deregulated Electricity Markets. PhD Dissertation. Department of Electrical Engineering and Computer Science. Massachusetts Institute of Technology. Cambridge, MA. June 2001.

Slaughter ES. 2001. Design Strategies to Increase Building Flexibility. *Building Research and Information*. Vol 29:3. pp. 208-217.

Spindler H, Glicksman L, and Norford L. 2002. The Potential for Natural and Hybrid Cooling Strategies to Reduce Cooling Energy Consumption in the United States. *RoomVent 2002*. Copenhagen, Denmark. pp. 517-520.

Standeven M, Bordass B, Leaman A and Cohen R. 1999. PROBE 18 Portland Building. *Building Services Journal*. January 1999. pp.E23-28.

Tan G and Glicksman LR. 2005. Application of integrating multi-zone model with CFD simulation to natural ventilation prediction. *Energy and Buildings*. In press. pp. 1-9.

Timmermans H, ed. 1993. *Design and Decision Support Systems in Architecture*. Kluwer Academic Publishers. The Netherlands.

Trigeorgis L. 1996. *Real Options: Managerial Flexibility and Strategy in Resource Allocation*. The MIT Press. Cambridge, Massachusetts.

USGBC (United States Green Building Council). 2002. *LEED Green Building Rating System, Version 2.1*. November, 2002.

Valenzuela J and Mazumdar M. 2001. On the computation of the probability distribution of the spot market price in a deregulated electricity market. IEEE Power Industry Computer Applications Conference. pp 268-271.

Van Paassen AHC and De Jong AG. 1979. The Synthetical Reference Outdoor Climate. *Energy and Buildings*. Vol. 2. pp.151-161.

Van Paassen AHC and Luo QX. 2002. Weather data generator to study climate change on buildings. *Building Serv. Eng. Res. Technol*. Vol. 23. No. 4. pp.251-258.

Vinnikov KY, Robock A, Basist A. 2002. Diurnal and seasonal cycles of trends of surface air temperature. *Journal of Geophysical Research*. Vol. 107, No. D22. pp.13-1 - 13-9.

Wang T and de Neufville R. 2004. Building Real Options into Physical Systems with Stochastic Mixed-Integer Programming. Proceedings of the 8th Real Options Annual International Conference. 17-19 June 2004. Montreal, Canada. http://www.realoptions.org/papers2004/de_Neufville.pdf.

Webster M, Forest C, Reilly J, Babiker M, Kicklighter D, Mayer M, Prinn R, Sarofim M, Sokolov A, Stone P, and Wang C. 2003. Uncertainty Analysis of Climate Change and Policy Response. *Climatic Change*. Vol. 61. pp. 295-320.

Wilson A, Uncapher J, Lisa M, Hunter Lovins L, Cureton M, and Browning W. (Rocky Mountain Institute). 1998. *Green Development: Integrating ecology and real estate*. John Wiley and Sons. New York, NY.

Wyon DP. 1996. Keynote Address: Indoor Environmental Effects on Productivity. *IAQ 96/Paths to Better Building Environments*. pp.5-15.

Xing H. 2004. Building load control and optimization. PhD Dissertation. Department of Architecture. Massachusetts Institute of Technology. Cambridge, MA.

Zmeureanu R and Pasqualetto L. 2000. Selection of Energy Conservation Measures in a Large Office Building Using Decision Models under Uncertainty. *Architectural Science Review*. Vol. 43. pp. 63-69.

Appendix A. Hybrid Binomial-Lattice Simulation Model for Value of Flexibility in Space-Use

This appendix provides notes on developing the base case “flexibility in space use” model. (File, for author’s reference: Binomial Lattice Model_BP Base Case.xls)

The following reference was used as a guide for setting up a binomial-lattice option valuation model in a spreadsheet: Copeland and Antikarov. 2001. Real Options: A Practitioner's Guide. p.206-214.

1. There are 5 basic worksheets to the “flexibility in space use” model: "event tree", "option tree", "option tree (2x)", "option tree (5x)" and "results." Change inputs in "results" worksheet. Results are also given on the "results" worksheet.
2. The model is set up with a total of 100 time steps. Any multiple of (years) times (divisions per year) that equals 100 can be used without modifying the spreadsheet.
3. To modify the spreadsheet for a different number of total time steps, do the following:
 - a. Input the Life of option (T) and steps per year (n) in the "Event Tree" worksheet.
 - b. Using the product of T*n, extend or contract the matrices on both worksheets (Event Tree and Option Tree) to be T*n columns times T*n rows (ex. T=10 years, n=12 time steps per year; T*n = 10*12 = 120; make both matrices 120x120).
 - c. In "Event tree," copy the row-zero formula across the entire row ($V_0 * u^{\text{col}} * d^{\text{row}} = V_0 * u^{\text{col}}$). Copy the formula ($d * \text{seed}$) throughout the entire matrix.
 - d. In "Option tree," copy the last column formula to the entire new last column. $=\text{MAX}(V-X,0)$
 - e. Next, copy the first row formula across the entire first row. $=\text{MAX}(V-X,C)$
 - f. Finally, copy the seed cell in (1,1) to the entire matrix.
 - g. Result of this basic model should compare to Black-Scholes formula.

4. The model is set-up to run 3 exercise costs simultaneously. Exercise cost is entered as a multiple of the initial underlying asset value. See worksheets "option tree," "option tree (2x)," and "option tree (5x)."

5. Monte Carlo simulation is used to model uncertainty in exercise date. Crystal Ball, a software plug-in to Excel available from www.crystalball.com, is used to perform Monte Carlo simulation. The simulation is conducted by defining a probability distribution for the "Life of option, T" variable on the "results" worksheet. The cumulative probability distributions for 5, 8, and 15 year time horizons, as determined with the case study partner, are given on the "results" worksheet. Upon performing a Monte Carlo simulation with Crystal Ball, the user must "create a report" and/or "extract data" to see the results of the simulation.

A.1 "results"

Change inputs in "results" worksheet.

1/A	B	C	1/D	E
2				
3	Model Input Values	Life of option (years), T	8	
4				
5	Annual risk-free rate, rf		0.05	
6	Current rent price (Vo) to calculate underlying asset value		25	
7	Annual standard deviation in rent price, σ		0.1	
8				
9				
10	Life of option (years), T - INTEGER		8	
11	Number of steps per year, n		10	---max n*T=100
12	Length of lease (years)		5	
13	Annual growth rate in rents (α)		0.1	---
14	OCC for lease		=PV_factor	
15	PV factor for lease			
16	Resulting current underlying asset value (lease price)		=D6*D15	
17	Resulting annual standard deviation in lease price, σ_{new}		=sigma_new	
18	Adjusted current underlying asset price: current		=D16+div tree!C12	
19	Annual growth rate in strike price (continuous compound)		0	
20				
21	Results			Option Value
22	Worksheet name	Ratio X/Vo	Binomial Lattice	Black Scholes
23	option tree	=option tree!\$C\$16	=option tree!\$C\$20	=option tree!\$I\$13
24	option tree (2x)	=option tree (2x)!\$C\$16	=option tree (2x)!\$C\$19	=option tree (2x)!\$I\$13
25	option tree (5x)	=option tree (5x)!\$C\$16	=option tree (5x)!\$C\$19	=option tree (5x)!\$I\$13
26				
27		Time chosen	=D3	

A.2 "event tree"

A.2.1. Input parameters

1/A	B	C
2	Event Tree for Underlying Asset	
3		
4		
5		
6		
7	Input Parameters	
8	Annual risk-free rate, rf	=LN(1+'option tree'!rf)
9	Current value of underlying (rent price), Vo	=Results!D6
10	Exercise price (renovation cost), X	= 'option tree'!X
11	Life of option (years), T	= 'option tree'!T
12	Annual standard deviation, σ	= 'option tree'!sigma
13	Number of steps per year	= 'option tree'!n
14	Total number of steps	=n*T
15	Annual std dev of lease (PV t years of rent payments)	=sigma*PV_factor

A.2.2. Calculated parameters

Calculated Parameters				
Up movement per step, u	=EXP(sigma_new*SQRT(T/(T*n)))		PV factor for lease	
Down movement per step, d	=EXP(-sigma_new*SQRT(T/(T*n)))	=1/u	OCC	=Results!D14
Risk free rate	=rf		PV factor	=(1-EXP(-19*t_rent))/19
Risk neutral probability (up), p	=(1+rf/n-d)/(u-d)			
Risk neutral probability (down), q	=1-p			
annual growth rate in rents α	0			
t_rent (lease duration)	=rent	Number of years of re		

A.3.3. Event tree calculation

	B	C	D	E	F
17	Event Tree for Underlying /				
18					
19		0	1	2	3
20	0	=Vo*PV_factor	=Vo_new*u^D\$19*d^\$B20	=Vo_new*u^E\$19*d^\$B20	=Vo_new*u^F\$19*d^\$B20
21	1		=C20*d	=D20*d	=E20*d
22	2			=D21*d	=E21*d
23	3				=E22*d

A.3 "option tree"

A.3.1. Input parameters

1/A	B	C
2	Binomial Lattice Model for	
3	Calculating Value of Real	
4		
5	Input Parameters	
6	Annual risk-free rate, rf	=Results!D5
7	Current rent price (Vo) to calculate underlying asset value	=Results!D6
8	Exercise price (renovation cost), X	=Vo*C16*EXP(Results!\$D\$19*T)
9	Resulting current underlying asset value (lease price)	=PV_factor*Vo
10	Adjusted current underlying asset price: current underlying + PV of dividend at exercise date	=C9
11	Life of option (years), T	=ROUND(Results!D3,1)
12	Annual standard deviation, s	=Results!D7
13	Number of steps per year	=Results!D11
14	Total number of steps	=n*T
15	Annual std dev of lease (PV t years of rent payments)	=sigma_new
16	Ratio X/Vo	1

A.3.2. Calculated parameters

1/D	E	F
2		
3		
4		
5		
6		
7	Calculated Parameters	
8	Up movement per step, u	=EXP(\$C\$15*SQRT(T/(T*n)) + \$F\$13/n)
9	Down movement per step, d	=EXP(-\$C\$15*SQRT(T/(T*n)) + \$F\$13/n)
10	Risk free rate	=rf
11	Risk neutral probability (up), p	=(1+rf/n-d)/(u-d)
12	Risk neutral probability (down), q	=1-p
13	annual growth rate in rents α	0
14		t_rent =Results!D12
15		
16		

A.3.3. Option value calculation

Value of American Call Option	B	C	D	E	F
17					
18					
19	0	1	2	3	
20	=IF(C\$19>\$C\$14,"",IF(C\$19=\$C\$14,MAX((X*event tree!C20),0),(p*option tree!D20+q*option tree!D21)/(1+rf/n)))	=IF(D\$19>\$C\$14,"",IF(D\$19=\$C\$14,MAX((event tree!D20-X),0),(p*option tree!E20+q*option tree!E21)/(1+rf/n)))	=IF(E\$19>\$C\$14,"",IF(E\$19=\$C\$14,MAX((event tree!E20-X),0),(p*option tree!F20+q*option tree!F21)/(1+rf/n)))	=IF(F\$19>\$C\$14,"",IF(F\$19=\$C\$14,MAX((event tree!F20-X),0),(p*option tree!G20+q*option tree!G21)/(1+rf/n)))	
21		=IF(D\$19>\$C\$14,"",IF(D\$19=\$C\$14,MAX((event tree!D21-X),0),(p*option tree!E21+q*option tree!E22)/(1+rf/n)))	=IF(E\$19>\$C\$14,"",IF(E\$19=\$C\$14,MAX((event tree!E21-X),0),(p*option tree!F21+q*option tree!F22)/(1+rf/n)))	=IF(F\$19>\$C\$14,"",IF(F\$19=\$C\$14,MAX((event tree!F21-X),0),(p*option tree!G21+q*option tree!G22)/(1+rf/n)))	
22			=IF(E\$19>\$C\$14,"",IF(E\$19=\$C\$14,MAX((event tree!E22+div tree!E21-X),0),(p*option tree!F22+q*option tree!F23)/(1+rf/n)))	=IF(F\$19>\$C\$14,"",IF(F\$19=\$C\$14,MAX((event tree!F22-X),0),(p*option tree!G22+q*option tree!G23)/(1+rf/n)))	
23					=IF(F\$19>\$C\$14,"",IF(F\$19=\$C\$14,MAX((event tree!F23-X),0),(p*option tree!G23+q*option tree!G24)/(1+rf/n)))

This cell's result is the option value

End

Appendix B. Uncertainty in amount of space model logic

In the ‘uncertainty in amount of space’ model, the total potential *renovation cost* consists of first meeting the space need with flexible space and then using inflexible space to meet any remaining need above the allocated flexible space. The logic statements for determining the applicable renovation costs (X_1 or X_2) are as follows:

IF $0 < \chi \leq a$, THEN $X_1 = \chi X_{flex}$

IF $a < \chi \leq 1$, THEN $X_2 = a X_{flex} + (\chi - a) X_{inflex}$

Where a is the allocated amount of flexible space chosen initially, χ is the total amount of space needed, X_{flex} is the renovation cost of flexible space and X_{inflex} is that for inflexible space. The total renovation cost (X_1 or X_2) is compared to the cost of renting the total amount of space needed. Renovating is chosen if

$$\chi S > X(1or2);$$

where S is the per unit rental price (i.e., cost of a lease). If renting is less costly than renovating ($\chi S > X(1or2)$), then renting is chosen, resulting in an option value of zero.

Figure 70 shows an example calculation when the space need (χ) is 0.66 and the amount of allocated space (a) is 0.4.

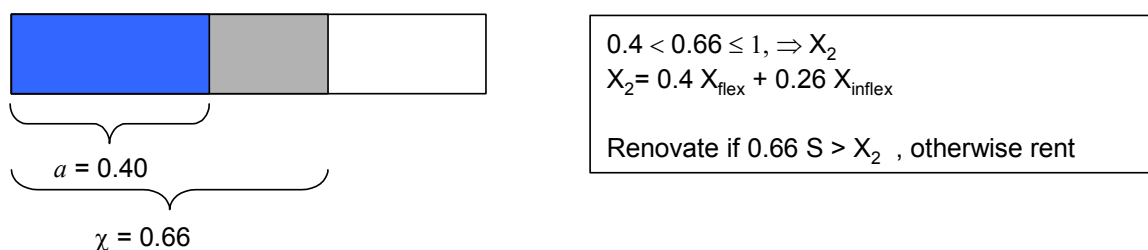
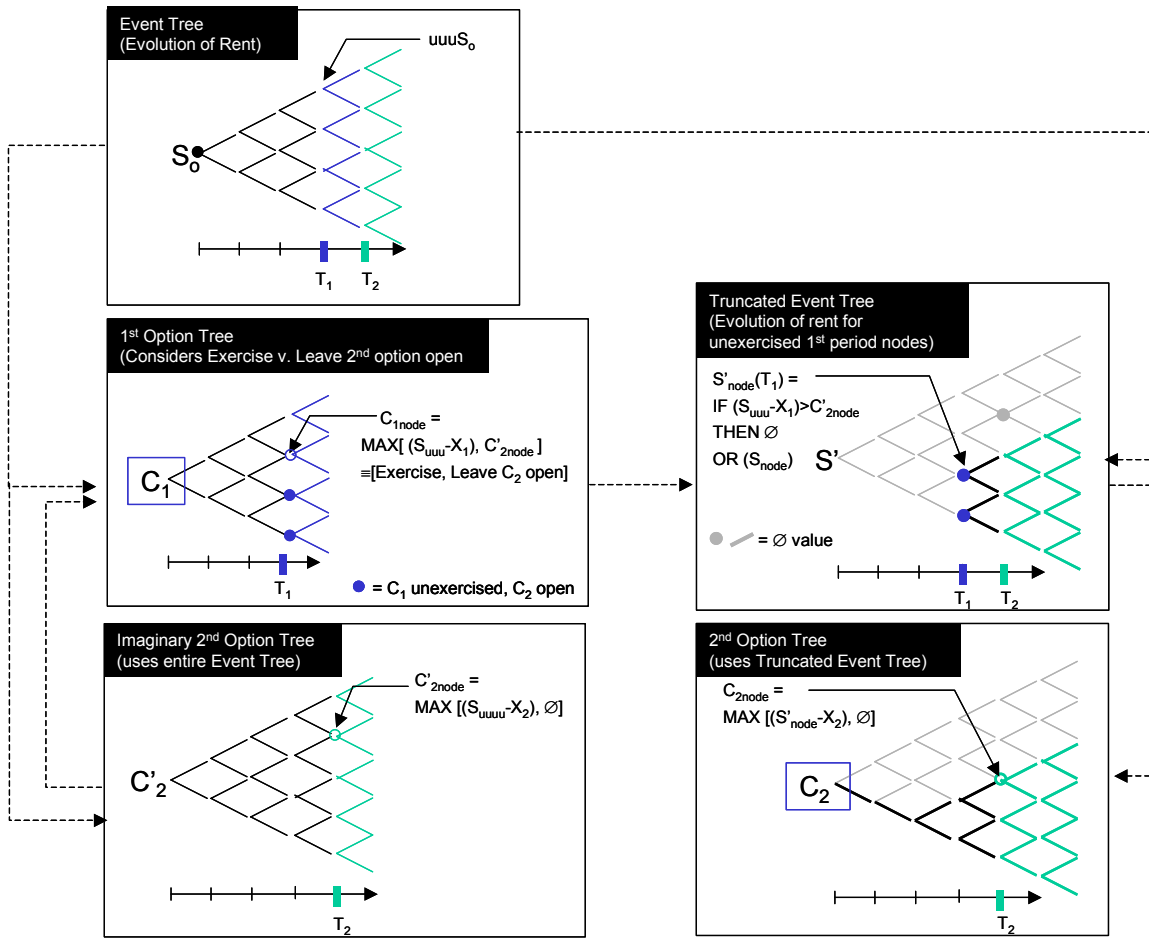


Figure 70. Example calculation for uncertainty in amount of space model.

Another possible version of the model that was considered allowed the space need to be noncontiguously by dividing it into both renovated and rented space. A noncontiguous means of providing space allows the managers to make use of flexible space where cost effective even if some of the remaining space need would be met using off-campus, leased space. In a noncontiguous version of the model, it would be permissible to meet the total space need by a) renting all the space, b) renovating all the space or c) both renovating and renting to meet the entire need. Such a scenario would provide information on the per unit value of flexible space subject to uncertainty in how much space is needed and independent of how much inflexible space would otherwise be included in the renovation.

Appendix C. Two-time period model logic

The figure below describes the logic of the compound model for two sequential times periods available for exercising the option to renovate.



In the 1st Option Tree, at the first exercise date, the decision is made to either exercise the option (renovate) or leave the option open for the second time period (rent). Renovating is chosen if the savings $(S-X_1)$ are greater than the corresponding imaginary second period option value at that node (C_2'), which is determined in the Imaginary 2nd Option Tree. The latter uses the full Event Tree, T_2 , and X_2 to calculate the option value (C_2') at each node, which is zero at the minimum. Once the end nodes of the 1st option tree are determined, the option value (C_1) is calculated as usual.

To calculate the true second period option value (C_2), a truncated event tree is needed. The Truncated Event Tree recognizes the states of nature (i.e., nodes where renting occurred, thus leaving the second option open) at T_1 for which, going forward, the second option may be considered. For the states of nature in which exercise occurred at T_1 , the second option period does not exist, and thus those nodes are truncated from the second period event tree. The truncated event tree starts at T_1 , and instead of a single initial point value, all nodes for which the second option is left open are the starting points, and those for which renovating was chosen are truncated. The evolution of rent in the second period emulates from these starting points, and, because it uses the same parameters as the fundamental event tree, the non-truncated node values match the fundamental event tree.

The 2nd Option Tree uses the Truncated Event Tree, T_2 , and X_2 to calculate the second period option value (C_2). The difference between the true 2nd Option Tree and the Imaginary 2nd Option Tree is that the imaginary tree uses the full event tree to calculate the nodal option values of the second period, whereas the true 2nd Option Tree uses the Truncated Event Tree. The second period option value is calculated as usual, with risk-neutral discounting back to the present time (T_0).

The total option value is the sum of C_1 and C_2 .

Appendix D: Other stochastic weather generator possibilities considered

Option value rests on the postulate that uncertainty is resolved over time. Thus, the time dependent component of the uncertain variables is of fundamental importance. For this reason, time series of (stochastic) weather evolution are needed, converse to typical building energy simulations that use ‘typical year’ meteorological data. Multiple sample paths of possible weather evolution are needed to model the uncertainty in the timing of the exercise (i.e., hot/humid period that results in uncomfortable interior conditions under natural ventilation). The hundreds of stochastically generated weather time-series are the stochastic inputs for the building energy simulation. The building energy simulator is run once for each weather time-series.

A literature review of stochastic weather generation found three basic classifications of models:

- a. Stochastic generation of weather statistically identical to observations (Kiraly and Janosi, 2002; Barrow and Lee, 2000; van Paassen and Luo, 2002; van Paassen and de Jong, 1979; Semenov and Barrow, 1997)
- b. Mathematical representation of weather as a stochastic process (Moreno, 2001; Pindyck, 1999) and
- c. Data from integrated atmospheric-ocean-land models (Levermore et al., 2004; Webster et al., 2003).

Building energy simulation requires hourly values of temperature and solar radiation data. An assessment of the feasibility of each type to a) integrate with the Java based building energy simulation program and b) to rapidly produce hundreds of stochastic time-series of temperature and solar radiation data reveals that development of a simplistic model was necessary.

Available models of the first type, stochastic generation of weather statistically identical to observations, do not produce hourly weather values. Many assumptions are needed to transform the daily average, minimum, and maximum values into hourly values. One

such method is to assume the data can be represented by a sine wave (van Paassen and Luo, 2002; Levermore et al., 2004). Assumptions are also needed to split global solar radiation into diffuse horizontal and direct normal (on a horizontal surface) components. The need to make many assumptions and conduct further data processing are the two major disadvantages of using available stochastic weather generators.

One mathematical representation of temperature (T) as a simplified stochastic process is mean reversion with noise:

$$T_{i+1} = T_i + (T_{i+1} - T_i) + \phi_i \quad (D.1)$$

where the subscript i represents the time step and ϕ_i represents the noise parameter. The noise parameter (ϕ_i) may further depend on reversion to the global mean average temperature (Moreno, 2001). Moreno (2001) compared temperatures produced by mean-reverting and autoregressive processes with noise to actual data in several locations for a period of one year, demonstrating that the goodness of fit is satisfactory. However, the distribution of noise is not homogenous through time; thus these basic processes are not satisfactory for simulating temperature (Moreno, 2001).

Use of the data produced by integrated atmospheric-ocean-land climate models is another possibility for input to building simulation. Levermore et al. (2004) at the Tyndall Center for Climate Change in the UK developed data for use in analyzing the performance of buildings in future years by combining data from global and regional (United Kingdom) climate models. In using global climate model output as input to building simulations, one primary consideration is to assure that the statistical properties of temperature and other relevant variables are satisfactory. Poor solar simulation in the regional climate model was one identified shortcoming of the use of such data (Levermore et al., 2004).

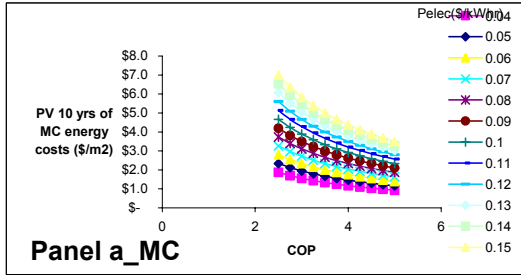
Another consideration is to assure that differences in scale in transferring data from global climate models to regional climate models does not result in skewed data. Thus, it is necessary to conduct extensive statistical analysis and assess the need for downscaling

adjustments before using climate model output as input for building simulation models (Levermore et al., 2004). Further development of data from global climate models is a promising way forward and is suggested as a future area of work for the U.S, as is being done in the UK. However, development of hourly data from climate models available for the U.S., for use to test the concept of options in building design, is outside the scope of this project.

Appendix E. Sample results of NVOV sensitivity to COP , P_{elec} , and r

The results shown in Figure 71 are for Seattle using the base case building parameters and original TMY2 data. The results are most sensitive to the parameters that display the largest spread in the charts (each set of charts (MC and HC) use the same scale on the y-axis). Thus, it is evident that the results are most sensitive to the price of electricity (panels a). Likewise panels c exhibit a large slope for a given discount rate, also indicating sensitivity to the price of electricity. The MC results are more sensitive to the discount rate than the HC results due to the four-fold difference in MC costs versus HC costs. Both sets of results are slightly sensitive to COP as seen in the slope of the lines in panels a and b for a given value of P_{elec} or r . Note also that the range of COP [2.5-5] is quite large, so sensitivity is even less than indicated in the charts when a narrower, more realistic range is considered.

Present value of 10 years of MC cooling energy costs using TMY2 data



Present value of 10 years of HC cooling energy costs using TMY2 data

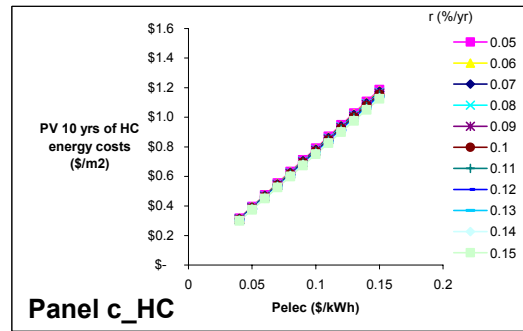
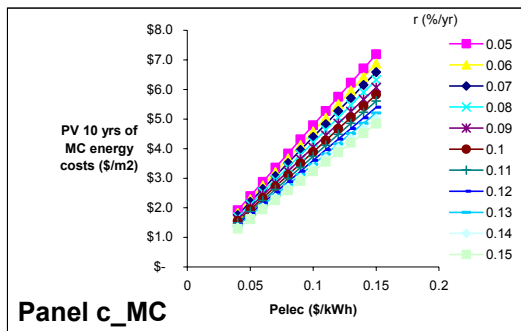
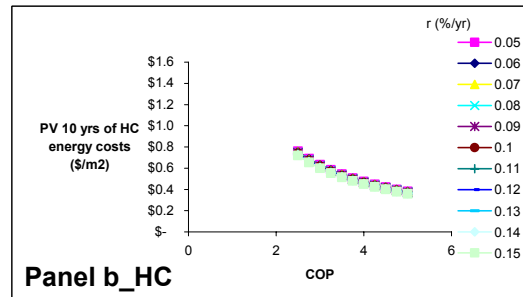
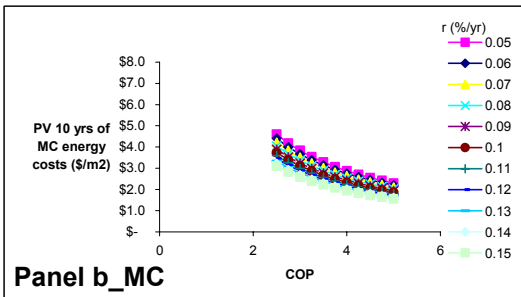
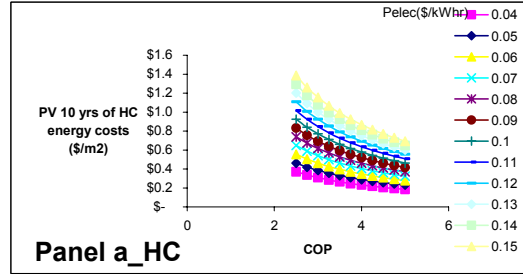


Figure 71. Sensitivity of the base case building's MC and HC cooling energy costs in Seattle to COP, P_{elec} and r .

Appendix F. Why modeled heating energy consumption is greater with NV than with MC

The heating energy consumption of the buildings with NV and HC is greater than the building with MC, as shown in Table 26. The relative difference increases as the NV airflow rate increases. However, even with increased NV airflow rate, *total* energy consumption is still less under NV and HC scenarios as compared to MC, as shown in Table 27.

The increased heating energy consumption indicated by the model for NV and HC cooling strategies is due to greater indoor air temperature swings in the naturally cooled buildings in the “shoulder” seasons (spring and fall) as a result of a single choice of the air change rate parameter. This would not necessarily be true in reality due to use of a dynamic control system. The simulation does not dynamically adjust the air change rate based on the amount of cooling needed. In any hour of the simulation, when the previous time step’s resulting indoor air temperature exceeds the “alert” maximum temperature and the current time step’s outdoor air temperature is less than the previous time step’s indoor temperature, the outdoor air is brought in at the rate specified in the parametric input. The resulting indoor air temperature may then be too cold, (i.e., too much cool outside air was brought inside), and heating will be needed in the subsequent time step to keep the indoor air at the minimum temperature of 16°C.

This NV indoor temperature flip-flop phenomenon is illustrated in Table 25 below, which shows results from the NV and MC buildings in Minneapolis on day 102 (March) from 10:00am – 4:00pm. The resulting NV indoor temperature at 10:00am is above the alert temperature of 26 °C in two sides of the building, and the 11:00am outdoor temperature (9.7°C) is (quite) sufficient for cooling. Thus, in the 11:00am time step, the outdoor air at 9.7 °C is brought in at a prespecified rate of 5 ACH. However, this is too much cooling, and 0.0053 kWh/m² of heating energy is needed to keep the indoor air at the minimum temperature of 16.0 °C. In the following time step, 12:00pm, no outdoor air is brought in

(because the 11:00am resulting indoor temperature is less than the alert maximum temperature), and thus the building once again becomes too warm on the south and east sides. This process repeats itself for the remainder of the day.

As seen in the table, in the MC building, cooling is only needed in the 10:00am hour, and only the amount of cooling necessary to keep the indoor air temperature at 28 °C is provided. In the hours of 12:00pm, 2:00pm, and 4:00pm, where the NV building is being opened to the outdoor air, the MC does not need cooling because the minimum outdoor air flow rate for air quality is providing enough cooling to keep the indoor air temperature less than 18°C. The MC air change rate is 15 liters/second/person, meaning that if the outdoor air temperature is less than the indoor air temperature, free cooling is provided without energy penalty. However, in the NV scenario, outdoor air is only brought in *if* the alert maximum temperature is reached. Thus, some hours in the NV scenario do not include any outdoor airflow in the energy equation. Furthermore, no heating is needed in any of these hours in the MC building because the heat inputs are balancing the heat loss so as to keep the indoor air temperature within the alert bounds on temperature (18-26 °C).

Table 25. Natural Ventilation simultaneous heating and ventilative cooling in the shoulder season.

Day 102 (March)	Outdoor Temp. (°C)	NV Indoor Temperature (°C)				NV Heating Energy (kWh/m ²)	MC Heating Energy (kWh/m ²)	MC Cooling Energy (kWh/m ²)
		north	south	east	west			
Hour								
10:00am	8.2	22.3	26.3	28.2	23.0	0	0	0.00011
11:00am	9.7	22.8	16.0	16.0	24.7	0.0053	0	0
12:00pm	11.3	22.4	29.8	27.8	23.4	0	0	0
1:00pm	12.9	24.0	16.0	16.0	25.4	0.0069	0	0
2:00pm	13.1	23.2	29.0	29.5	24.4	0	0	0
3:00pm	13.3	23.9	16.0	16.0	25.5	0.0053	0	0
4:00pm	14.4	23.8	30.2	30.0	28.0	0	0	0
5:00pm	14.9	23.4	16.0	16.0	18.1	0.0048	0	0

Results from file "Results_MSP00000_022105.xls", hours 2434-2440

Table 26. Annual heating energy results for the base case building for MC, NV, and HC cooling strategies for various values of NV air change rate.

Inputs				Results - annual heating energy										
Location	Bldg notes	No. trials	No. yrs	T_{max} (K)	N (hrs)	n (hrs)	ACH for NV (roomful s/hr)	σ (oC)	σ (oC/yr)	MC htg energy (kWh/m ²)	NV htg energy (kWh/m ²)	HC htg energy (kWh/m ²)	(NV-MC) /MC	(HC-MC) /MC
SEA	Default	1	1	301	120	30	5	0	0	20.11	23.57	22.58	17.2%	12.3%
SFO	Default	1	1	301	120	30	5	0	0	5.20	8.27	7.82	59.2%	50.6%
CHI	Default	1	1	301	120	30	5	0	0	58.80	61.95	61.35	5.4%	4.3%
MSP	Default	1	1	301	120	30	5	0	0	86.82	89.70	89.30	3.3%	2.9%
MSP	Default	1	10	305	8000	7000	2	0	0	86.82	87.18	87.25	0.4%	0.5%
MSP	Default	1	10	305	8000	7000	10	0	0	86.82	95.09	93.69	9.5%	7.9%
MSP	Default	1	10	305	8000	7000	5	0	0	86.82	89.70	89.30	3.3%	2.9%
CHI	Default	1	1	305	8000	7000	2	0	0	58.80	59.12	59.19	0.6%	0.7%
CHI	Default	1	1	305	8000	7000	10	0	0	58.80	67.47	65.75	14.8%	11.8%
SEA	Default	1	1	305	8000	7000	2	0	0	19.96	20.22	20.28	1.3%	1.6%
SEA	Default	1	1	305	8000	7000	10	0	0	19.96	30.42	27.51	52.4%	37.8%
SFO	Default	1	1	305	8000	7000	2	0	0	5.20	5.42	5.58	4.4%	7.4%
SFO	Default	1	1	305	8000	7000	10	0	0	5.20	15.27	12.53	193.9%	141.1%

Table 27. Annual total energy consumption results for the base case building for MC, NV, and HC cooling strategies for various values of NV air change rate.

Inputs				Results - total htg + clg energy										
Location	Bldg notes	No. trials	No. yrs	T_{max} (K)	N (hrs)	n (hrs)	ACH for NV (roomful s/hr)	σ (oC)	a (oC/yr)	MC tot energy (kWh/m ²)	NV tot energy (kWh/m ²)	HC tot energy (kWh/m ²)	(NV-MC) /MC	(HC-MC) /MC
SEA	Default	1	1	301	120	30	5	0	0	39.80	23.57	26.45	-40.8%	-33.6%
SFO	Default	1	1	301	120	30	5	0	0	30.34	8.27	13.71	-72.7%	-54.8%
CHI	Default	1	1	301	120	30	5	0	0	93.00	61.95	77.59	-33.4%	-16.6%
MSP	Default	1	1	301	120	30	5	0	0	111.88	89.70	99.54	-19.8%	-11.0%
MSP	Default	1	10	305	8000	7000	2	0	0	1,118.76	871.82	1,075.20	-22.1%	-3.9%
MSP	Default	1	10	305	8000	7000	10	0	0	1,118.76	950.87	1,020.87	-15.0%	-8.7%
MSP	Default	1	10	305	8000	7000	5	0	0	1,118.76	896.98	995.38	-19.8%	-11.0%
CHI	Default	1	1	305	8000	7000	2	0	0	93.00	59.12	87.89	-36.4%	-5.5%
CHI	Default	1	1	305	8000	7000	10	0	0	93.00	67.47	78.40	-27.4%	-15.7%
SEA	Default	1	1	305	8000	7000	2	0	0	38.19	20.22	32.07	-47.1%	-16.0%
SEA	Default	1	1	305	8000	7000	10	0	0	38.19	30.42	30.95	-20.4%	-19.0%
SFO	Default	1	1	305	8000	7000	2	0	0	30.34	5.42	22.52	-82.1%	-25.8%
SFO	Default	1	1	305	8000	7000	10	0	0	30.34	15.27	18.23	-49.7%	-39.9%

Appendix G. NVOV User Interface

This is an early version of the user interface, and it reflects all of the design parameters applicable to the building thermal simulation. Revision was still going on at the time of thesis publication regarding user inputs for the NVOV “Simulation Parameters” and “Real Options Decision Parameters.”

NVOV The Natural Ventilation Option Valuator - Input File																				
Directions: modify inputs designated by blue text																				
Experiment Title:	SEA_J_00a25s4_100trials																			
Descriptive note or objective:	test a high value of "a" to see if exercise is induced																			
Experiment completed?	yes or no																			
Variable	Value	Units	Suggested Default Value	Options/Range	Notes															
Simulation Parameters																				
Total number of years in trial	10	years	10	1-?																
Number of trials	100	---	100	1-?																
Name/location of results file	/C:/Documents and Settings/Lara/My Documents/NVOV/TMY data Meteorom/Formatted for NVOV/SEA00000.xls																			
Real Options Parameters																				
Exercise Decision Rule																				
Maximum (hourly) indoor temperature for natural ventilation + option (NVO) building	301	(K)	301		300K=27oC; 301K=28oC; 302K=29oC; 303K=30oC;															
N: the total number of hours in the 'sliding' assessment window	620	(hours)	620	[1-?]	620hrs=4weeks of hours															
n: number of hours within the window which cannot exceed the maximum temperature	224	(hours)	224	n<=N	224hrs=1/3 of the hours in 4weeks															
Cost Calculations																				
Discount rate	0.1	/year	0.1	[0.00-?]																
Price of electricity	0.08	\$/kWh	0.08	[0.01-?]																
COP of chiller	3	---	3	[1.0-?]																
Climate inputs																				
σ: Standard deviation of mean daily temperature	0	°C	0	[0.01-?]	Std deviation of a normally distributed random variable, data from Vinnikov et al for SEA and ORD															
a: Annual rate of increase in average temperature	0	°C/yr	0	[0.00-?]	Analysis from IGSIM for the city's latitude band and the appropriate number of years (defined by total years in the experiment)															
Name/location of TMY2 input file	/C:/Documents and Settings/Lara/My Documents/NVOV/SEA_SeattleWA/ResultsJ_SEA00a25s4_100trials.xls																			
Building description																				
Geometry																				
North-South length of building	30	(m)	54																	
East-West length of building	54	(m)	30																	
Room depth	15	(m)	15		1/2 of East-West length															
Room width	54	(m)	54		entire North-South length															
Room height	2.7	(m)	2.7																	
Orientation	north	---	north	north, south, east, west	Does not affect energy calculations for well-mixed case															
Airflow																				
Indoor air well mixed, or not	TRUE		TRUE	TRUE, FALSE	TRUE = "well mixed indoor air," FALSE = "little indoor air mixing"															
Mechanical air change rate	15	(L/s/person)	15	0-?	Air change rate provided by mechanical system while building is sealed															
Natural ventilation air change rate	5	(roomfuls/hr)	5	0-?	Air change rate due to natural ventilation when building is open															
Shading, thermal mass, and insulation																				
Thermal mass	high	---	none, if nothing specified	none, low, standard, high	Assumed to be in floor															
Overhang depth	1	(m)	1	0-?	0 indicates no overhang															
Insulation type	foam	---	foam	foam, fiberglass																
Insulation thickness	0.01	(m)	0.01		Does not affect thermal mass															
Windows																				
Window area, percentage	100	%	100	[0-100]	the percentage of the room wall (exterior façade) that the window takes up (8 options total: Single-, double-, and triple-glazed windows with or without blinds (6 of the 8); Inside Ventilated and Outside Ventilated double-glazed windows with an extra pane on the inside or outside, which together create an air channel that houses the window blinds (2 of the 8).															
Window typology	blinded double glazed	---		clear, low-e, super low-e, blue, bronze, green, gray																
Window glazing type	low-e	---	low-e		(7 options: clear, low-e, super low-e, blue, bronze, green, and gray)															
Blinds																				
Blinds width	0.025	(m)	0.025		as viewed in section															
Blinds daytime schedule	respond to solar intensity	---	respond to solar intensity	responds to solar intensity, responds to temperature, always open, always closed																
Blinds nighttime schedule	always open	---	always open	always open, always closed																
Blinds absorptivity	0.38	---	0.38 (white plastic)	[0.0-1.0]	See table.															
Blinds emissivity	0.8	---	0.8 (white plastic)	[0.0-1.0]	See table.															
<table border="1"> <thead> <tr> <th>Blinds Type</th> <th>Absorptivity</th> <th>Emissivity</th> </tr> </thead> <tbody> <tr> <td>Shiny Aluminum</td> <td>0.20</td> <td>0.22</td> </tr> <tr> <td>White Plastic (default)</td> <td>0.38</td> <td>0.80</td> </tr> <tr> <td>Painted Silver Aluminum</td> <td>0.45</td> <td>0.45</td> </tr> <tr> <td>Blue Plastic</td> <td>0.85</td> <td>0.90</td> </tr> </tbody> </table>						Blinds Type	Absorptivity	Emissivity	Shiny Aluminum	0.20	0.22	White Plastic (default)	0.38	0.80	Painted Silver Aluminum	0.45	0.45	Blue Plastic	0.85	0.90
Blinds Type	Absorptivity	Emissivity																		
Shiny Aluminum	0.20	0.22																		
White Plastic (default)	0.38	0.80																		
Painted Silver Aluminum	0.45	0.45																		
Blue Plastic	0.85	0.90																		
Loads																				
Occupancy load	0.1	(people/m2)																		
Equipment load	5	(W/m2)																		
Lighting requirement	400	(lux)																		
Control																				
Lighting control	efficient	---	efficient	efficient, inefficient	"efficient" means lights (lux) are varied to supplement sunlight; "inefficient" means all lights are fully on or off															
Upper "set point" temperature on thermostat	28	degrees Celcius	28	>upper alert	Upper bound on actual indoor temperature for mechanically cooled building (including hybrid cooled) building															
Upper alert temperature telling building to take "cooling" action (open windows for NV/HC or turn on AC for MCHC)	26	degrees Celcius	26	>lower alert	Indoor temperature at which action is taken to mitigate further rise in indoor air temperature															
Lower alert temperature telling building to take "heating" action	18	degrees Celcius	18	>lower set point	Indoor temperature at which action is taken to mitigate further decrease in indoor air temperature															
Lower set-point temperature on thermostat	16	degrees Celcius	16	16 is recommended low	Lower bound on actual indoor temperature for all building types															

Appendix H. Values for α and Δ_O

As derived in section 5.3.1, the following tables provide the mean values for the ratio α (the percentage change in mean option value to the exercise costs) and Δ_O (the mean option value for \$0/m² exercise costs) for each case examined in this study. The ratio α is calculated using the results for exercise date t as follows:

$$\alpha = (1 - (1 + r_i)^{-t}) / (1 + r)^{-t} \quad (\text{Eq. 5.13 from Ch. 5})$$

The mean value of α for each case is reported in the following tables.

Example calculation: Minneapolis base case

The mean value of α for the Minneapolis base case (C) is 0.36. Thus, for exercise costs of \$10/m², the delayed/avoided equipment costs portion of option value is

$$\Delta_E = \alpha \chi E_{MC,o} = (0.36)(\$10/m^2) = \$3.60/m^2 \quad (\text{Eq. 5.14 from Ch. 5})$$

The mean value of cooling energy cost savings Δ_O is \$3.49/m². Thus, the total option value for exercise costs of \$10/m² is calculated as

$$\Delta = \Delta_E + \Delta_O = \$3.60/m^2 + \$3.49/m^2 = \$7.09/m^2 \quad (\text{Eq. 5.8, 5.10-11 from Ch. 5})$$

Rounding produces slight errors.

Seattle			
Case	Δ_O	α	Exercise
A	\$ 3.02	63%	48/99
B	\$ 3.19	100%	0/100
C	\$ 3.19	100%	0/100
D	\$ 3.13	NA	0/1
E	\$ 3.20	100%	0/100
F	\$ 3.37	98%	2/100
G	\$ 3.19	100%	0/100
H	\$ 3.38	100%	0/100
J	\$ 3.68	47%	86/100

San Francisco			
Case	Δ_o	α	Exercise
A	\$ 3.96	47%	68/100
B	\$ 4.39	100%	0/100
Da	\$ 4.39	NA	0/1
Db	\$ 4.38	NA	0/1
E	\$ 4.47	100%	0/100
F	\$ 4.73	99%	1/100
G	\$ 4.40	100%	0/100
H	\$ 4.67	100%	0/100

Chicago			
Case	Δ_o	α	Exercise
A	\$ 3.27	3%	100/100
Ab	\$ 3.06	0%	100/100
B	\$ 5.98	100%	0/100
Ba	\$ 3.15	0%	100/100
C	\$ 5.00	52%	60/100
D	\$ 5.85	0%	1/1
E	\$ 3.33	4%	100/100
F	\$ 2.69	1%	100/100
G	\$ 5.97	100%	0/100
H	\$ 4.10	17%	98/100
la	\$ 3.85	80%	28/100

Minneapolis			
Case	Δ_o	α	Exercise
A	\$ 4.40	100%	0/100
Ab	\$ 2.62	3%	100/100
Ac	\$ 3.15	20%	93/100
B	\$ 4.40	100%	0/100
Ba	\$ 2.62	1%	100/100
C	\$ 3.49	36%	80/100
D	\$ 4.35	NA	0/1
E	\$ 3.48	32%	85/100
F	\$ 2.19	3%	100/100
G	\$ 4.40	100%	0/100
Ga	\$ 4.37	98%	2/100
Gb	\$ 4.09	72%	39/100
H	\$ 3.38	26%	89/100
la	\$ 2.89	98%	2/100
lb	\$ 3.46	80%	27/100

Appendix I. Literature review of stochastic electricity pricing models

A literature review of electricity pricing models is provided to support future development of a compound option model describing the option to install MC and/or operate MC based on both a) comfort and b) energy prices. Several authors have studied and proposed models for electric power spot prices (Skantze, 2001; Davison et al., 2002; Alvarado, 2000; and Valenzuela, 2001). Two factors drive price volatility or “price spikes” of the electrical power market. First, electrical power cannot appreciably be stored, and system stability requires constant balance of supply and demand (Skantze, 2001). Second, most users of electricity are, on short time scales, unaware of or indifferent to its price (Davison et al., 2002). The probability distribution of prices depends on many factors, such as the secular trend and periodicity of demand, temperature and other meteorological influences, and the loading order of generating units (Valenzuela and Mazumdar, 2001).

Davison et al. (2002) construct a model for electricity spot prices for the purpose of pricing forward and options contracts on spot electricity, where accurate representation of price spikes is essential. The authors used four criteria to develop the model: price spikes exist, off-peak electricity prices are often zero, electricity prices are sometimes negative, and electricity prices do not drift indefinitely. (The authors do not provide further explanation for the drivers of zero and negative spot electricity prices.) A switching model for spot prices is constructed. Realizations of spot electricity price are drawn from one of two probability distributions with “switching” between the distributions. The probability density of the model as a whole is a mixture of the two distributions. Only one regime is in effect at a given time. Switching models of this type are mean reverting in that the conditional probability of a price falling given that it is high is very large. Assumptions are needed for the probability of a price spike ε , the price spike distribution, and the low price distribution. The last two are modeled as normal distributions. The probability of a price spike is dependent on the relationship between demand and supply, which are modeled as sine and step functions respectively as a function of time. A

random variable is drawn from a uniform distribution $[0,1]$. If the realization of the random variable exceeds the value of ε given by the demand/supply relationship, then a value for the spot price of electricity is drawn from the price spike distribution; if not, a value is drawn from the low price distribution.

Skantze (2001) and Valenzuela and Mazumdar (2001) use a different approach to modeling spot electricity prices. In contrast to Davison et al. (2002), these authors model demand and supply as stochastic variables. Skantze (2001) also uses the model to study derivatives contracts in the power supply industry. These authors begin with the rationalization that electricity price stochasticity is driven by the underlying stochastic nature of supply and demand. Demand is a random quantity because electricity consumption is based on human behavior and ambient temperature, among other things. Supply is also a partially random variable because generating units have the potential to fail, as one example. Skantze (2001) models spot electricity prices as an output of supply and demand, which include the underlying processes of outdoor temperature, economic growth, fuel prices, and unexpected plant failures to model supply and demand. Valenzuela and Mazumdar (2001) also develop a stochastic model for the spot market price of electricity based on the underlying processes of demand and supply, but fewer underlying processes are considered. They assume that the spot price at a specific hour t is equal to the operating cost (\$/MWh) of the last loaded generating unit used to meet the demand prevailing at that hour.

Alvarado and Rajaraman (2000) studied observed data to understand volatility in spot prices of electricity. They use a Fourier Transform procedure to a) find periodic harmonics in (deregulated) spot electricity prices and b) separate the random component from the periodic variation components. Then, making the assumption that the random component follows an ordinary Wiener process with a normal distribution of price differences, they estimate the standard deviation. Using the imputed standard deviation, or volatility, an artificial price process is generated using a time step of 1-day and assuming that there is no drift. This was found to be unsatisfactory, so mean reversion and jump processes (also with mean reversion and a separate probability for upward

jumps than for downward jumps) were added. The authors find this model to be close to replicating actual price behavior. Using their model, Alvarado and Rajaraman (2000) analyzed 2000 bus locations in the system of study to determine average monthly prices and volatilities at each bus location. Most of the locations have approximately the same volatility in prices, but 83 of the 2000 exhibit significantly higher volatility in their prices. No location exhibited significantly lower volatility than the system volatility.

Because option value as defined in Chapter 5 is linear with respect to the price of electricity, it is not fully necessary to model stochastic realizations of electricity price to determine its impact on option value. More research would be needed to understand how realization of price spikes correspond to outdoor temperature, as outdoor temperature is also an important determinant of the NVO building's performance. As discussed, with a properly functioning, well-designed control strategy, the cooling loads of a HC building will not be greater than the cooling loads for a comparable MC building. Furthermore, it is not likely that lower electricity prices will be realized if a building's electric power is obtained from a large scale utility, as supply and demand issues indicate that price will not fall without significant increases to generation capacity. Thus, price spikes or otherwise greater realization of electricity prices will serve to increase option value for the simulated results presented this thesis, which were based on a conservative average price of electricity.