FACING REALITY: DESIGN AND MANAGEMENT OF FLEXIBLE ENGINEERING SYSTEMS

by

Michel-Alexandre Cardin

Honors B.Sc. in Physics, McGill University, 2001
M.A.Sc. in Aerospace Science and Engineering, University of Toronto, 2003

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Signature of Author……………………………………………………………………………
Technology and Policy Program, Engineering Systems Division,
May 18th, 2007

Certified by……………………………………………………………………………………
Richard de Neufville
Professor of Engineering Systems
Chairman, Engineering Systems Division Education Committee
Thesis Supervisor

Accepted by…………………………………………………………………………………...
Dava Newman
Professor of Aeronautics and Astronautics and Engineering Systems
Director, Technology and Policy Program

"Stay committed to your decisions, but stay flexible in your approach"

Tom Robbins, American Novelist, b. 1936

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Abstract

This thesis proposes a practical approach to defining flexible design and development strategies for maximizing the expected value of engineering systems. Specifically, the approach deals with the fact that it is generally computationally impractical to explore all the possible ways a system might be developed and operated, given the large number of possible scenarios in which the system might evolve. To make the analysis tractable within the computational resources available, it proposes that designers and program managers use a catalog of representative operating plans built from combinations of design elements and management decision rules. These are associated with a range of possible scenarios of uncertain variables that might affect the system's expected value and performance.

This work develops the novel methodology introduced by (de Neufville, 2006) to guide the search for catalogs of operating plans while aiming at minimizing computational effort. It assumes a model of the engineering system is available, together with several value/performance metrics such as Expected Net Present Value (ENPV) and Value At Risk and Gain (VARG). It uses an algorithm based on statistical experiment design, Adaptive One-Factor-At-a-Time (OFAT) (Frey and Wang, 2006; Wang, 2007), to search the combinatorial space in light of system's responses to a limited set of uncertain variable scenarios. Two case studies demonstrate the benefits of the analysis methodology. One is inspired from the development of a parking garage near the Bluewater commercial center in the United Kingdom. The other relates to the development of a real estate project in the United States.

Results from case studies show improvement compared to inflexible design of engineering systems while still requiring minimal computational effort. This, together with appropriate policy recommendations, provides incentives for dissemination of the analysis methodology in industry and government. The simplicity of the methodology and use of tools already familiar to the firm and government agency alleviate political barriers to implementation. It allows designers and program managers to remain within established framework, rules, and management constraints. It favors transparent presentation and efficient application to design and management of engineering systems, thus allowing program managers to present the natural evolution of decisions to senior decision-makers.

Thesis supervisor: Richard de Neufville
Professor of Engineering Systems

Acknowledgments

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I am grateful to Mr. John Dahlgren from the MITRE Corporation for providing the financial support necessary to this research, and for initiating this great research opportunity together with Dr. de Neufville. I am hoping this work will contribute positively in disseminating ideas about flexibility in the engineering and management communities.

I would like to thank my father Michel for exposing me to the world of real estate development since I was a kid, and for contributing to the spark that led to one of the case studies presented in this thesis. I am grateful to my mother Marjolaine as well as my sisters Marie-Ève and Sophie-Catherine for being so supportive, intrigued, and understanding of my effort. I want to thank all of you for encouraging me and supporting me during the good and the hard times of the last two years.

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journey the most enjoyable, enriching, and empowering experience of my life. I hope we will stay connected the longest time possible.

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Chapter 1 – Introduction

Designers of engineering systems always seek for better approaches to improve the value and performance of a system. They seek the best combinations of design elements and management decision rules before selecting a particular design. In doing so, they assume one particular evolution of the uncertain variable(s) affecting their system over its intended useful life. For instance, they may assume that prices for a given product will increase at a constant rate over the intended lifetime of the system, evaluate which combination of design elements and management decision rules extracts most value from this particular future, and work to satisfy design requirements accordingly.

One problem with this approach is that the future is uncertain. The uncertain variables affecting the value and performance of the system may turn out completely different than originally assumed. Therefore, it is possible that designers choose a design configuration that performs extremely well under the scenario originally assumed, if it occurs, but very poorly if reality turns out otherwise.

If designers consider several scenarios of the uncertain variables before committing to a particular design, another problem emerges. In addition to considering several possible combinations of design and management decision rules under a particular scenario, they need to find the best combination for each possible scenario of the uncertain variables. This is because design choices can differ depending on the scenario under consideration.

The number of possible combinations of design elements, management decision rules, and uncertain variable scenarios can become intractable very rapidly. If flexibility is considered as a way to adapt the system to take even more advantage of unexpected upside opportunities, or to reduce losses in case of downside events, the problem becomes even larger and harder to tackle.

A Real Life Example

A real situation experienced recently by a colleague who visited Codelco, Chile's national copper extraction company, exemplifies the above issues with more realism. The Chuquicamata and Rio Tumic mines in Chile's north region are well known for their copper deposits. The mining systems are good examples of the complexity inherent to the design and management of primary resource extraction systems. Operations require various sizes of truck fleets and crushing mills, complex networks of transportation routes, different extraction plans to reach the ore, etc. Mining companies are also very vulnerable to large fluctuations in prices, which is the uncertain variable affecting value and performance of their system. This makes flexibility an attractive feature to increase profits when prices are high and in the opposite case, to reduce losses.

The visitor to Codelco noticed that over years of operation, the company had been constantly developing new and creative ways to operate the mine. One thing they had not fully exploited was the use of this portfolio of operations in the preliminary analysis stage to determine better investment strategies at any given time and given certain copper price scenarios. The reason for this were large costs in terms of time, human, and computer resources necessary for the analysis compared to a small budget dedicated to preliminary project analysis. Hence, the cost and burden of the analysis precluded the search for potentially more profitable ways to exploit the mine. In addition, great sources of flexibility that could have added even more value were being left aside.

Proposed Solution

This thesis addresses the issues presented above to insert more realism in design of engineering systems. It suggests an analysis methodology that creates a limited set of relevant future scenarios for the uncertain variables affecting the system, and a structured approach for exploring the possible combinations of flexible designs and management decision rules under each particular scenario. This approach leads to a design choice that is more suited to different future scenarios, which clearly improves overall value and performance of the system. It also allows program managers to operate the system in different ways, depending on the behavior of the uncertain variable observed at any given time.

The analysis methodology is proposed in the context where computational power has tremendously increased in recent years. It recognizes that it is impossible to explore exhaustively all possible combinations of design elements and management decision rules. It suggests however that given recent progresses in computer technology, designers now have the opportunity to explore more design and management possibilities at a minimal and affordable increase in analytical cost.

Excel® is the software used in this thesis to demonstrate applications of the analysis methodology. This software is very simple to manipulate, understand, and is widely used in the engineering and management communities. Monte Carlo simulations are used to illustrate the benefits of the approach on two realistic case studies of engineering system design and management. The first one is inspired from the development of a parking garage near the Bluewater commercial center in the United Kingdom. The second is based on the development of a real estate site in the United States.

This thesis also has a policy component that considers three main barriers to implementation of the methodology in industry and government. The stakeholder analysis proposes recommendations to alleviate these barriers, with most solutions being inherent parts of the methodology. The first barrier is the typical difficulty to implement new methodologies in firms and government agencies, especially when existing rules have been used for a long time. Methodological "lock-in" creates inertia that is difficult to surmount. The second barrier is because the methodology imposes more analytical burden, although it is largely compensated by improved computer technology. The third barrier is the lack of incentives for program managers to implement the analysis methodology.

The document is structured as follows. Chapter 2 introduces the concept of *catalog of operating plans*, one of the most important concepts in this thesis, in the context of designing and managing flexible engineering systems. Chapter 3 describes the analysis methodology that is at the heart of the thesis. It also describes a method for finding representative scenarios of uncertain variables relevant to the analysis, the search algorithm adaptive One-Factor-At-a-Time (OFAT) used to create the catalog, and an analytical method used to assess the value of the catalog of operating plans. Chapter 4 applies the methodology to two realistic case studies, and develops results that support the proposed methodology. Chapter 5 presents the policy component of the thesis, which deals with the main barriers to implementation in real world practice. Chapter 6 offers potential avenues for future research.

Chapter 2 – Design and Management of Engineering Systems

2.1 Reality Meets Practice

2.1.1 The Reality

Figure 2.1 describes the reality facing designers and program managers in developing and managing complex systems. In the initial design phase, designers may consider many possible combinations of design elements and management decision rules to accomplish the system's goal. Design elements are the constituent parts that create the system as a whole, while management decision rules represent possible behaviors to manage and operate the system. In the Codelco case presented above, examples of design elements can be the choice of crushing mills sizes and number of truck fleets necessary to operate the mine. Examples of management decision rules can be to use a particular set of crushing mills and truck fleets more suited to the exploitation of a particular area of the mine.

The Figure 2.1 section on uncertain variables represents the fact that uncertainty can affect system performance in many ways. In this thesis, an uncertain variable is a variable outside of designers and program managers' control that can affect the value and performance of the system. Price and demand are good example of uncertain variables.

Such variables can take on different behaviors over the course of a project's useful life. Each manifestation of the variable over the project's useful life creates one *uncertain variable scenario*. Figure 2.2 shows an example of uncertain variable scenario relevant to the Codelco example where the evolution of copper price per metric ton is depicted over a certain period of six years. This scenario represents one of many price behaviors that could have occurred over the same period.

Initial Design	Uncertain Variables	Managers Adjust	Lifetime Performance
Physical infrastructure (Many possibilities)	Price, demand for services (Many possibilities)	Best use of existing facilities; development of additional facilities (Many possibilities)	Realized net present value, rate of return, etc. (Many possibilities)

Figure 2.1: Reality faced by designers and program managers in the development and operations of complex systems. (Source: de Neufville, 2006).

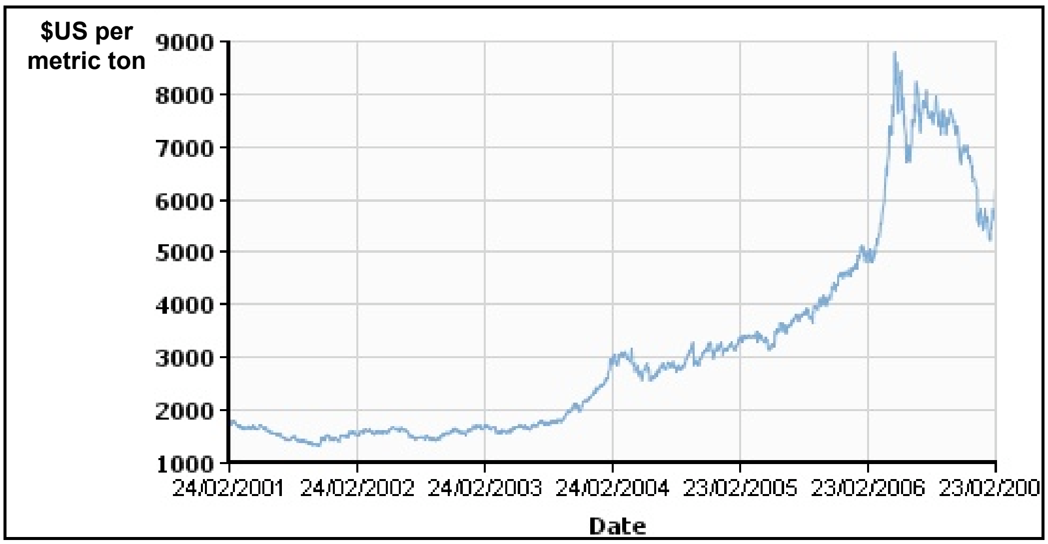


Figure 2.2: Example of uncertain variable scenario. In this case, the uncertain variable is price of copper per metric ton in U.S. dollar. This is one price scenario among many that could have occurred over the same time period. (Source: London Metal Exchange, 2007).

Once a good combination of design elements and management decision rules is found, a design is selected and developed. Operations of the system by program managers follow as seen on Figure 2.1 in the section on managers' adjustments. Given the system design at hand, program managers choose between a large number of possible *operating plans* to operate the system. They also adjust operations depending on observed conditions in the uncertain variables.

Because the concept of operating plan is very important in this thesis, the analysis of Figure 2.1 is paused here to explain this concept in greater detail. An operating plan is a way to manage and operate a system that combines a particular set of design elements and management decision rules under a particular uncertain variable scenario. For example, in the mining industry, given a scenario where prices are increasing, the goal of an operating plan may be to extract the ore from an area of the mine where copper is easily accessible so that revenues can be generated easily. This operating plan combines design elements such as large truck fleets to carry the ore, and large size crushing mills to extract as much as possible of the desired metal. These design elements are combined with management decisions that favor mining in a particular sequence to maximize copper extraction while minimizing the distance between the site and the crushing mills. This operating plan is chosen because it maximizes value when prices are high. It may however be suboptimal when prices are decreasing because mine operations for large production might be more costly, and not sustainable when prices are low.

Since mining sites can be exploited in different sequences, with different numbers of trucks, possible routes between the site and crushing mills, and available sizes of crushing mills, a large number of operating plans can be created. Each operating plan is ideally tailored to a specific price scenario. Since a large number of price scenarios exist, there is a large number of possible operating plans program managers can select to operate the mine. All of these possibilities are represented in the section on managers' adjustment in Figure 2.1.

Another example of operating plan is in the airline industry. In this case, given a scenario where fuel prices are increasing, the airline managers might decide to service destinations where demand is high, and where locations are concentrated near a central "hub" (or central airport) to minimize long flights. In this case the airline may choose smaller aircraft types to minimize fuel expenditures. Again, program managers may select from a wide array of destinations and aircraft types to create operating plans that are suited to particular price scenarios, and extract as much value as possible uncertain conditions.

Now coming back to the analysis of Figure 2.1 in the section on lifetime performance, the operating plan adopted by the program manager gives rise to a certain value or realized performance of the system for the project's lifetime, and given uncertain conditions. This can be measured, for instance, in financial terms like Net Present Value (NPV), internal rate of return, or through other non-financial metrics such as number of lives saved, etc. In the case of Codelco, this is measured as realized profit in any given year. Again, since many operating plans exist under a large number of uncertain variable scenarios, many different measures of lifetime performance can arise.

2.1.2 In Practice

Unfortunately in practice, value assessments rarely correspond to lifetime performance measures as projected in the last section of Figure 2.1. Value and performance of the system depend on its technical reliability, and on how well managers adjust to uncertain variable conditions.

If enough computational, financial, and time resources were available, designers would like to consider all possible combinations of design elements, uncertain variable scenarios, and management decision rules before deciding on a final design that permits a large array of operating plans. They would do so in order to find a design that can suit most uncertain conditions. In reality however, it is difficult and time consuming, if not at all impossible computationally, to explore this *combinatorial space* for all possible combinations.

In this thesis, the concept of combinatorial space represents the spectrum of all possible combinations of design elements, management decision rules, and uncertain variable scenarios that designers can investigate to find the best design under all possible manifestation of uncertainty. Even if only a few possibilities exist for each element, the space can become intractable analytically quite rapidly. For instance, assuming Codelco designers represent the uncertain price variable with five possible values over the course of a twenty years project (low, mid-low, medium, mid-high, high), this means $5^{20} \approx 95$ trillions scenarios need to be considered for the price variable only. If designers consider combinations of design elements and management decision rules best suited for each price scenario, the design problem becomes completely intractable.

To address this problem, current practice for the design and management of engineering systems often assumes inflexible design requirements, one uncertain variable scenario, and one particular operating plan in order to choose a system's design (Figure 2.3). Even though this choice may provide a good cash flow to assess value and performance, it may not be the best one available.

Initial Design	Uncertain Variables	Managers Adjust	Lifetime Performance
Physical infrastructure (Many possibilities)	Price, demand for services (1 scenario for each)	Best use of existing facilities; development of additional facilities (1 operating plan)	Realized net present value, rate of return, etc. (1 cash flow)

Figure 2.3: Schema of current practice for the design and management of a complex system. (Source: de Neufville, 2006).

2.2 Introducing the Concept of Catalog of Operating Plans

In order to move to a more complete analysis, designers may explore the effect of a limited set of uncertain variable scenarios on their choice of design elements and management decision rules. They wish to do so without having to find the optimal combination for each possible manifestation of the uncertain variable.

That is, considering that a very large number of possible uncertain variables scenarios exist (95 trillions in the previous example), designers would like to select a limited set of representative scenarios to guide their search for the best combination of design elements and management decision rules.

By studying the effect of this limited set of uncertain variable scenarios on the choice of design elements and management decision rules, designers may now find solutions that are more realistic and adaptable to uncertainty. For instance, by selecting three copper price scenarios – increasing, constant, and decreasing – among the 95 trillions available, Codelco may decide to incorporate sizes of crushing mills and truck fleets in the design of the extraction system that are more suited to adapt towards these price scenarios. Even though the case of three scenarios is fairly limited, the resulting design is already more realistic and suited to uncertainty than if only one scenario is selected.

Choosing particular combinations of design elements and management decision rules suited to this collection of uncertain variable scenarios creates a limited set of operating plans suited for each scenario under study. This limited set of operating plans forms a *catalog of operating plans*, where each operating plan is suited to a particular scenario of the uncertain variables. Program managers may then use the catalog of operating plans to adjust the system more efficiently depending on observed uncertain conditions. Even if each design is not perfectly tailored to each price scenario in the Codelco example, operations of this mining system may be more profitable than one that is only suited for one particular manifestation of copper price.

The following examples clarify these concepts. For instance, if observed copper prices are found to be on the rise as in the example on operating plans of Section 2.1.2, program managers may decide to operate the mine by focusing on ore that is readily available so it can be sold quickly and at a high price. In effect, they may "pick" an operating plan combining design elements and management decision rules to accomplish this particular goal. If prices are decreasing, a different operating plan focusing on getting rid of the overburden can be used so that ore can be easily extracted when prices are back on the rise. These ideas are shown in Figure 2.4.

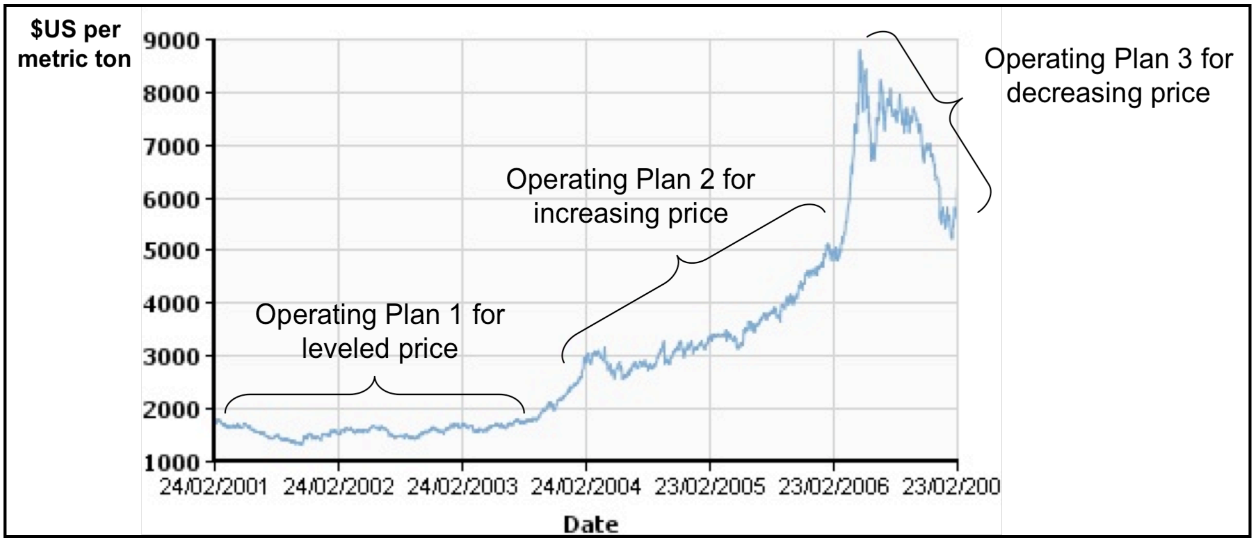


Figure 2.4: Use of a catalog of operating plans for managing a mine depending on observed trends in copper prices (London Metal Exchange, 2007). The NPV achieved using a limited number of operating plans compares to the ideal situation where managers can adapt in a perfectly tailored fashion to each uncertain variable scenarios.

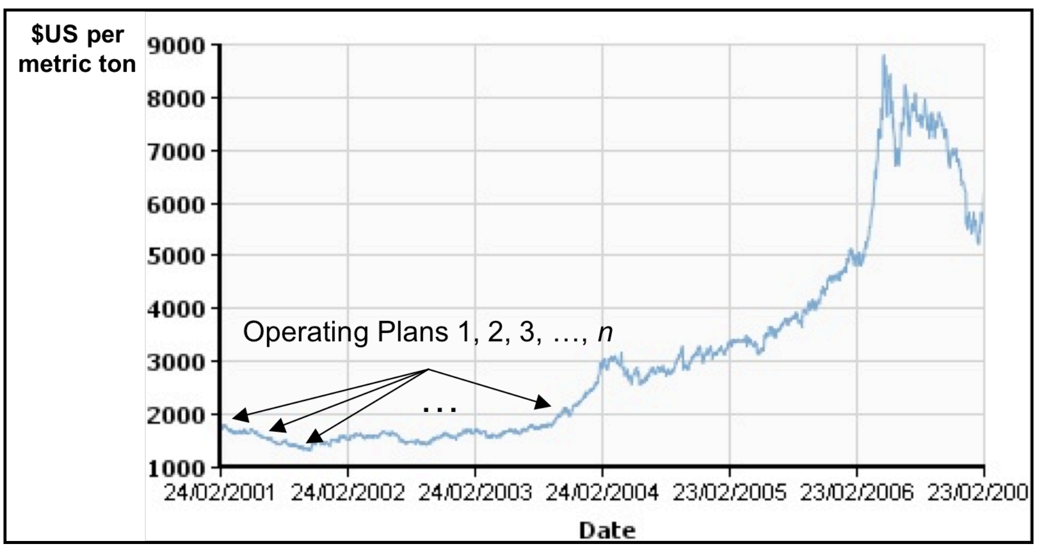


Figure 2.5: Perfectly tailored operating plans represent an upper bound on the highest achievable NPV for a given system. A catalog of operating plans tries to approximate this ideal situation with fewer operating plans.

This catalog of operating plans compares with the ideal situation when management can adapt perfectly to all possible uncertain variable scenarios. In this ideal situation, shown in Figure 2.5, there are as many operating plans as the number of possible fluctuations in the uncertain variables. The design and management rules chosen extracts maximum value from each situation. In other words, the ideal situation provides operating plans that are perfectly tailored to the uncertainty affecting system's output and performance.

The goal of this thesis is to introduce an analysis methodology that helps finding the catalog of operating plans that gets as close as possible to the ideal situation above, given that limited time and computational resources are available. In other words, it aims at being as effective as possible in the search for the best catalog given these limitations. This analysis methodology is presented in Chapter 3.

It is important to note however that the catalog of operating plans does not aim at describing the entire set of possible ways in which the system can be designed and operated. Rather, it represents a crude short-cut measure that enables designers to conduct a more realistic analysis within feasible computational means, compared to assuming a single fixed scenario of the uncertain variables. This approach increases chances of finding the most valuable design by exploring the combinatorial space further. It does so recognizing the impossibility of assessing exhaustively the value of all possible solutions in the combinatorial space. Figure 2.6 summarizes the role of the catalog of operating plans in current practice for the design and management of engineering systems.

Initial Design	Uncertain Variables	Managers Adjust	Lifetime Performance
Physical infrastructure (Many possibilities)	Price, demand for services (Many possibilities)	**A Catalog of a major possible responses** (Some possibilities)	Realized Net Present Value, Rate of Return, etc. (Many possibilities)

Figure 2.6: Role of catalog of operating plans in the design and management of complex systems (de Neufville, 2006).

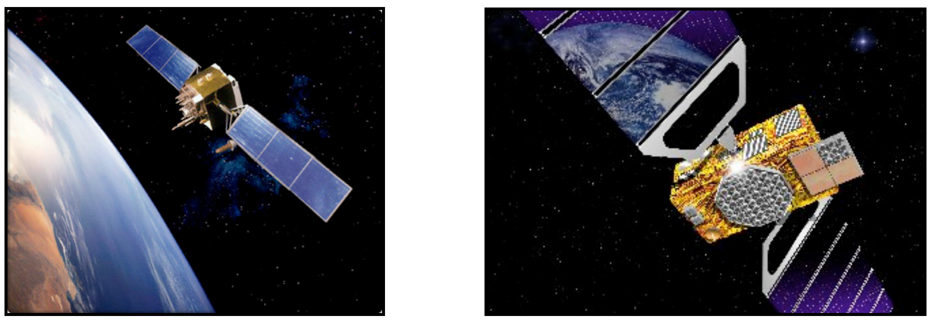
2.3 The Role of Flexibility

As briefly mentioned in the Introduction section, flexibility allows program managers to adapt their system towards uncertain conditions so that additional value and performance can be extracted. Since it plays a very important role in this thesis, the concept is presented in further details here.

As outlined in the two historical examples below, flexibility inherent to a system allows adaptation to unexpected circumstances in a relatively efficient manner. In other cases, adjustments or a lack thereof may be more costly. The Boeing B-52 Stratofortress is an excellent example of a system flexibly designed (Figure 2.7). Developed in the 1950s, it was able to adapt to unexpected changing conditions a number of years later in several occasions. The aircraft was originally designed to carry heavy and cumbersome nuclear warheads at high altitude (Montulli, 1986). The aircraft's large-scale belly was one of the main design features to accomplish this. A few years later, the Soviet air defense incorporated surface-air missiles, which forced the aircraft to fly at lower altitude. The belly was then reconfigured to carry air-launched cruise missiles to defend the aircraft through such mission (Boyne, 2001; Dorr and Peacock, 1995). This low-altitude capability was used later on during the Vietnam War to assist ground troop operations.

Figure 2.7: The flexible design of the Boeing B-52 Stratofortress's allowed adaptation to changing warfare environments. (Source: Dorr and Peacock, 1995).

On the other hand, the Navstar Global Positioning System (GPS) (Figure 2.8a) is an example of a lack of flexibility that turned out costly in terms of missed opportunities for the U.S. Department of Defense (DoD) and U.S. Government. No flexibility was built in the system to possibly collect user fees at a later time. Considering today the vast array of commercial applications that make use of GPS, this represents a huge missed opportunity the Europeans are trying to avoid in designing their GALILEO system (Figure 2.8b). In effect, the European positioning system is planned to collect user fees for greater accuracy and precision, depending on geographic location.



a) b)

Figure 2.8: a) GPS represents a system designed inflexibly, and a considerable missed commercial opportunity. (Source: Boeing, 2007) b) The European GALILEO system will charge user fees for higher precision and accuracy. (Source: Directorate General European Commission, 2007).

There are typically two types of flexibilities in engineering systems. Those can be classified as sources of flexibility "in" projects and "on" projects (de Neufville, 2005). The former exploits technical aspects of the design to build flexibility "in" the system. It requires input from technical people and designers to produce a design that is different than an original, inflexible one. For example, (de Weck et al., 2004) argue that a staged deployment of satellites and the flexibility to redeploy them in different orbits would have helped the Globalstar and Iridium satellite phone systems to reduce losses when demand for satellite phones turned out lower than expected. The technical flexibility required in each satellite to redeploy in different orbits is an example of flexibility "in" the system.

Flexibility “on” projects relates to all management decisions that can be made to affect the system as a whole without necessarily modifying technical design components. As summarized by (Kalligeros, 2006), there are several sources of flexibility at this level. For instance, program managers may decide to defer investments altogether to obtain more information about market conditions. When several projects are available, this may also involve deferring initial choice of investment project. Abandoning a project altogether if exogenous conditions are unfavorable is also an important flexibility “on” projects. It is also possible to expand or reduce production to accommodate demand and price, and finally, combine all or some of the above options to create a compound real option. Flexibility “on” projects also includes the flexibility in the operations of the system. For example, an airline may decide to operate different routes in a flexible manner so it concentrates inbound and outbound flights where demand is higher.

In this thesis and the analysis methodology presented in Chapter 3, flexibility plays a very important role. In considering the best combinations of design elements and management decision rules suited to uncertain variable scenarios, designers may introduce flexibility to adapt even more effectively towards uncertainty and increase overall value and performance of the system. This allows program managers to adapt even more efficiently to uncertainty in the section on manager’s adjustments of Figure 2.1. In order to do this, analytical tools are needed to screen the engineering system for sources of flexibility. This is necessary to determine which set of flexibility is worth including in the system’s design, and to justify to program managers and senior management the additional cost required for implementation.

2.4 Screening the Engineering System for Sources of Flexibility

While several methodologies exist to deal with flexibility “on” projects, such as those presented by (Brennan and Trigeorgis, 2000; Dixit and Pindyck, 1994; Luenberger, 1997; Schwartz and Trigeorgis, 2001; Trigeorgis, 1996 & 1995), there is a community devoted to the finding of sources of flexibility “in” project design. Important contributions and approaches are described below.

Kalligeros (2006) used Design Structure Matrices (DSM) to represent the engineering system and the interaction between its different components. An algorithm known as Invariant Design Rule (IDR) is developed to find standard components in the system, also known as platform components. Those are components of the system that do not change when the system evolves or is adapted to suit a slightly different purpose. In this method, the basic assumption is that non-standard components in the system, or those that vary when applying the IDR, are potential sources of flexibility. A method to assess the value of non-standard components is also suggested and based on real options analysis. A case application to oil platform development is used to demonstrate the benefits of the approach.

Bartolomei (2007) presented the Engineering System Matrix (ESM) to represent the engineering system and its socio-technical components and intricacies (Figure 2.9). The ESM is an improvement to existing system-level modeling frameworks like DSM because it provides a dynamic, end-to-end representation of an engineering system. From a matrix perspective, an ESM is made of traditional DSMs with the addition of system drivers and stakeholders DSMs. The system drivers component of the ESM represents the set of uncertain variables affecting the system that are out of managers' control. The stakeholders component represents the different stakeholders involved in operating and managing the system, as well as those that benefit (or pay) for its use.

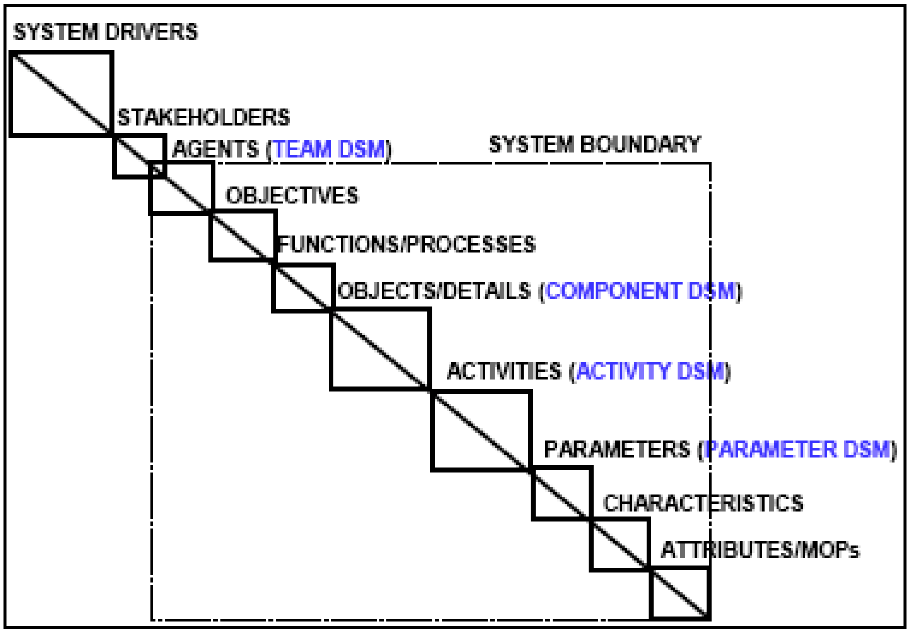


Figure 2.9: The Engineering System Matrix (ESM), which is a combination of standard DSMs with system drivers and stakeholders DSMs. (Source: Bartolomei et al., 2006).

Once the system is adequately represented by an ESM, Bartolomei suggested that "hot" and "cold" spots can be used as sources of flexibility "in" the system. Those are elements that are respectively crucial and less crucial to make the system function well. One qualitative method for finding a hot spot in an ESM is to focus on the number of links and interactions between it and other components of the matrix. The more connections, the more a change in that particular component of the system will affect the entire system's well functioning.

Bartolomei's suggestion is that since a "hot" spot greatly affects the well-functioning of the system, acquiring flexibility to smooth out a possible change in such component will add value to the system. For example, suppose it is found in a particular ESM that the managing director of the system in the stakeholder DSM has many links to it. It is found however that the managing director will take an indeterminate leave-of-absence within two weeks, greatly affecting the final outcome of the project. Therefore, acquiring flexibility in that area by hiring a temporary director or training another employee can enhance the value of the project as compared to functioning without a managing director.

Silver and de Weck (2006) introduced an algorithm based on switching cost minimization and a reaching algorithm optimization technique to find potential platforms across various initial system designs. Switching cost is defined as the cost of switching from one system design to another through flexibility to adapt to changing conditions in uncertain variables. It is included in life cycle cost together with design cost, operating cost, and fixed cost. For example, if demand is the uncertain variable, switching cost is the cost of switching from a lower production supply chain to higher production. It may include technical costs as well as the cost of training new personnel and managers to get acquainted with the new production line.

The methodology introduces a few possible initial designs for the system and produces several scenarios of the uncertain variable (e.g. demand) under which the system could perform. The algorithm then seeks the design or set of designs that minimizes life cycle cost over the project duration and across the scenarios. The lower the switching cost, the more often a switch occurs between designs depending on the set of uncertain variables modeled as scenarios. The authors suggest that identifying the elements in design that need to be changed to switch from one design to the other represent non-standard components that can be further exploited as potential sources of flexibility. They therefore suggest finding technical means to implement this flexibility so that switching can be done in the cheapest possible way. A case study to Lunar-Mars exploration missions is used as an example to demonstrate the benefit of the approach, and for the choice of initial design between four different launch vehicle designs.

Cardin et al. (2007) proposed a methodology based on historical case studies of engineering systems and Kalligeros' IDR method to help program managers and designers screen their system for flexibility. It also proposes tools for assessing their value prior to incorporation in the system design and operations based on Monte Carlo simulations (see Section 3.4 below). The goal is to structure managers' thinking in how they can approach the search for new sources of flexibility. The method is based on five flexible design attributes, or engineering lessons, extracted from historical studies of the Boeing B-52 Stratofortress, Navstar Global Positioning System (GPS), Convair B-58 Hustler, as well as the U.S. Air Force/NASA Inertial Upper Stage (IUS) program. These attributes are platform-like initial design, adaptability for changing missions, adaptability for changing purpose of the system, technological evolvability and maintainability, as well as design modularity.

Finally, de Neufville (2006) indicated that flexibility can be found in existing facilities by changing and adapting operations of the system. This is another source of flexibility in systems not investigated explicitly by the above authors, who concentrate on flexibility acquired upstream "in" the system design.

2.5 Considering Designers' Reality

One last important issue to consider in laying grounds for the analysis methodology of Chapter 3 is designers' reality. Either in industry or in government, their goal is to explore the combinatorial space for design elements and management decision rules that provide best value and performance given uncertain conditions. Meanwhile, they have to do so spending a limited amount of time, computational resources, and financial resources. In other words, they cannot spend too much time doing simulations and reviewing models before presenting their design or recommendations to program managers and senior decision-makers.

The catalog approach accounts for this by reducing the size of the combinatorial space to interesting design elements and management decision rules, and by structuring the search more efficiently given one particular uncertain variable scenario. This structured approach helps designers sending a clear message to decision-makers by using analytical tools and software familiar to the firm or government agency. This transparency makes it much easier to assess a project's financial value, and for it to be accepted.

In addition, when presenting a particular solution to senior decision-makers, program managers need to deliver a clear, efficient, and easily understandable message. This reality prevents use of several methods described in Sections 2.4 to screen the system for sources of flexibility, and of methods to assess the value of flexibility. For instance, valuation methods such as real options analysis based on binomial trees have a hard time making it to real world technical practice (e.g. engineering, real estate, architecture) because they involve understanding new methods and quantitative concepts a firm is probably not familiar with (Geltner, 2007). Screening methods based on DSM (Kalligeros, 2006; Bartolomei, 2007; Bartolomei et al. 2006) are complex and demanding to apply in reality, especially when large engineering teams need to agree on every part of the analysis. Techniques based on optimization such as the one presented by (Silver and de Weck, 2006) may lack transparency and appear as a "black box answer" based on optimization results.

Because clarity is important when communicating ideas, especially to higher management levels, the method introduced in the next chapter promotes exploration of the combinatorial space that is both efficient and transparent. Valuation methods based on Monte Carlo simulations are suggested for use in this methodology. This is because they show transparently the evolution of design and management decisions with financial instruments and software already familiar to the firm. This should encourage further exploration of the combinatorial space for solutions that potentially lead to increased value and performance compared to current design practice, which does not necessarily account in advance for flexibility.

Chapter 3 – Enabling Practical Search for the Catalog of Operating Plans

This thesis proposes an analysis methodology to explore efficiently the combinatorial space of operating plans that improves value and performance of engineering systems compared to inflexible design and management practice. It structures the search for the best design and management decision rules around catalogs of standard operating rules, which act as short cuts for the analysis. The use of these catalogs minimizes the cost, time, and computer resources devoted to upfront modeling, simulations, and financial assessments.

The proposed method uses intuitive analytical tools that can be understood easily by the firm or government agency's program managers and senior decision-makers. To demonstrate the value of the method, Chapter 4 applies it to two real world case studies.

3.1 Analysis methodology

The methodology uses analytical tools already present in a firm, industry, or government sector to analyze and value new engineering system designs. It works with models and concepts familiar to management to favor adoption. In this thesis, design analysis is done in Excel®, which is widely used both in government and industry. It is important to note however that the methodology applies independently of the analytical tools used. It also structures thinking about flexibility in design and management of the system. This should contribute in adopting the most valuable catalog of operating plans to improve value and performance of the system. The methodology consists of five steps:

Step 1: Build an initial model of the engineering system to measure value and performance. Designers need to identify the main design elements and management decision rules related to their system, as well as a metric for assessing its value and performance under different combinations of those. They also need to identify the main sources of uncertainty, or uncertain variables, affecting value and performance.

An initial model of the system is developed here from a series of fixed requirements on design elements, uncertain variables, and management decision rules. A preliminary analysis of the value and performance of the system is made using deterministic projections of the uncertain variables.

Step 2: For each source of uncertainty, propose a limited set of uncertain variable scenarios and review initial model. A limited set of uncertain variable scenarios is introduced in the model as a way to recognize how uncertainty may affect the value and performance of the system. An example of uncertain variable scenario in the Codelco case can be a particular price pattern over the lifetime of a mining project.

This limited set of scenarios consists of relevant scenarios to designers who want to find how initial design elements and management decision rules can change depending on the scenario under consideration. Relevant scenarios can be found using the method suggested in Section 3.2. Brainstorming, judgment, and practitioners' expertise are also necessary to determine those relevant scenarios. If need be, designers review their model in light of new information brought by the use of those scenarios.

Step 3: Determine the main sources of flexibility in the system and incorporate in the model. Sources of flexibility to adapt to the limited set of uncertain variable scenarios are identified here using any of the screening methodologies of Section 2.4, together with experts' brainstorming sessions, judgment, and expertise. The benefit of introducing flexibility at this stage is to adapt the system even more effectively to changes in uncertain conditions, and therefore capitalize on upside opportunities while reducing potential losses due to downside events. Valuable flexibilities are incorporated in the model representation of the system.

Step 4: Search the combinatorial space and create the catalog of operating plans. The goal here is to find the combination of design elements and management decision rules that provides best value and performance of the system for each relevant uncertain variable scenario considered in step 2. All sources of flexibility from step 3 are used in this analysis to measure performance given a particular scenario. For each scenario, the best combination of design elements and management decision rules forms an operating plan, and the collection of operating plans arising from the analysis of each scenario forms the catalog of operating plans.

For each uncertain variable scenario from step 2, the search for the best combination of design elements and management decision rules is structured by applying the experiment design algorithm adaptive OFAT (Frey and Wang, 2006; Wang, 2007). This algorithm is described in greater detail in Section 3.3.1.2.

Step 5: Assess the Value of the Catalog of Operating Plans. Designers assess here the expected value and performance achieved using the catalog of operating plans of step 4. The method for doing this is described in Section 3.4.

This analysis determines how much value the catalog of operating plans adds compared to a system that recognizes uncertainty but is inflexibly designed and managed. This information is useful to program managers wishing to use this catalog of operating plans to manage their system. They may find how much value, on an expected value basis, can be added compared to using only one inflexible operating plan. Since only a few scenarios of uncertain variables are used in exploring the combinatorial space, they can identify, using historical data, which trend is currently occurring in the uncertain variable, and "pick" the most relevant plan for a particular trend observation.

3.2 Finding Relevant Uncertain Variable Scenarios

In step 2 of the analysis methodology, designers need a method to find uncertain variable scenarios that are most relevant to their analysis. To tackle this issue, this thesis suggests creating several simulations of possible uncertain variable scenarios, and analyzing them to uncover particular characteristics that can be used to classify them in a small number of categories. These categories should be chosen to represent most uncertain variable scenarios that can arise in reality. Simulations of uncertain variable scenarios can be done in Excel®.

An example involving the development of a parking garage is used to illustrate these ideas. In this example, inspired from (de Neufville et al., 2006), the service provided is parking space for cars near a commercial center. Demand for parking space is the uncertain variable providing revenues to the owner of the garage. For the purpose of this brief example, readers need not consider the costs of the project.

The proposed approach has three parts. The first part uses deterministic projections of the uncertain variables used in step 1 of the analysis methodology. It determines how fluctuations can be incorporated around deterministic projections based on the analyst's assumptions of relevant probability distributions. An example of simulated demand scenario for the parking garage example is shown in Figure 3.1. It is assumed that demand is the only uncertain variable in this example.

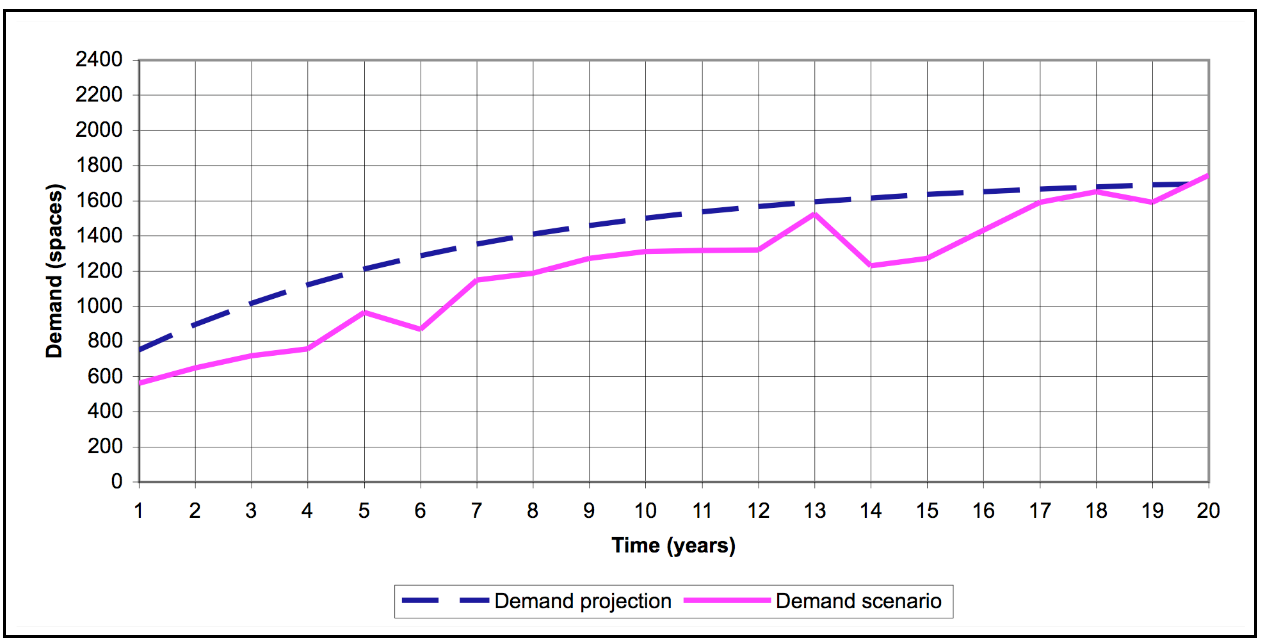


Figure 3.1: Example of simulation of the uncertain demand variable around projected trend for the parking garage example.

The second part involves simulations of several scenarios, and visualization of them for further analysis. Depending on designer's need, ten or fifty simulations might be necessary for the next part. Simulations can be laid out as shown in Figure 3.2.

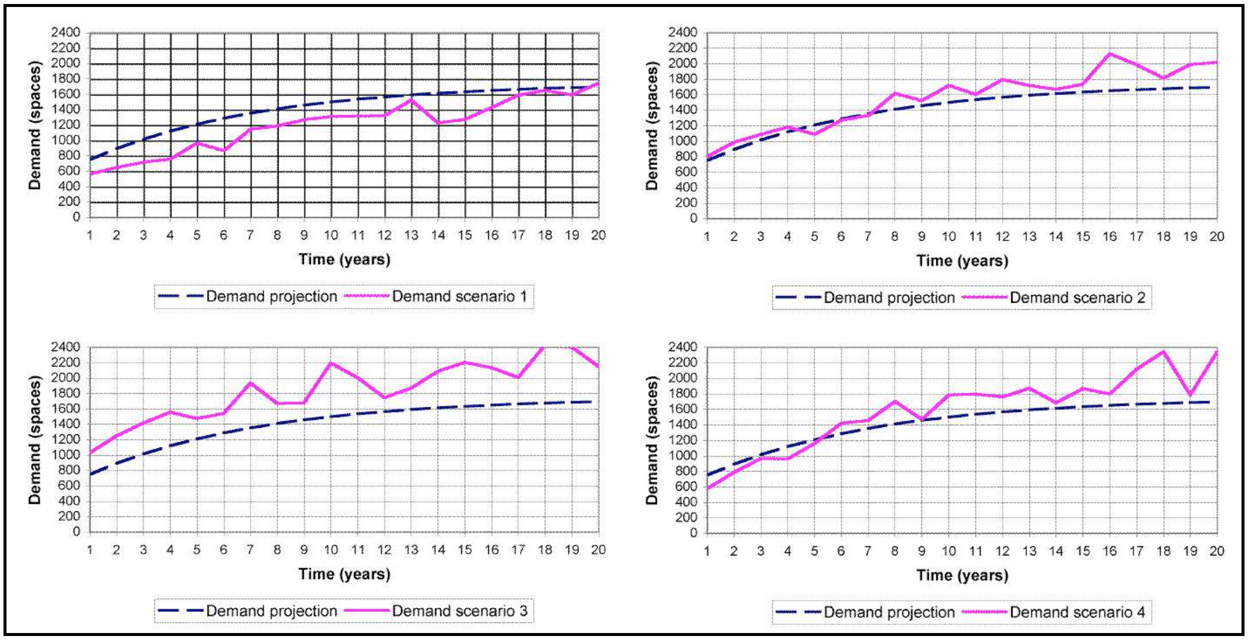


Figure 3.2: Examples of simulated demand scenarios in the parking garage example. Designers analyze these scenarios in part three to find characteristics that enable classification in categories representing the diversity of possible demand scenarios. Only four scenarios are shown here, but designers are free to choose as many as necessary to uncover representative categories.

The third part analyzes the scenarios to discover particular characteristics useful for categorization. These characteristics should ideally allow categorization of the entire set of possible uncertain variable scenarios that can emerge in reality. For example, designers may classify scenarios in Figure 3.2 by looking at the percentage growth between the first and final years, and by looking at the initial value of the scenario. Four categories could be created: low initial value and low growth, low initial value and high growth, high initial value and low growth, and high initial value and high growth. These characteristics are also used to classify simulated uncertain variable scenarios in step 5 of the analysis methodology to assess the overall expected value of the catalog of operating plans. A simple algorithm can be implemented in Excel® to classify each pattern in this part of the analysis.

3.3 Searching the Combinatorial Space

The search algorithm for exploring the combinatorial space for the most relevant catalog of operating plans was originally developed in the context of statistical experiment design (Frey and Wang, 2006; Wang, 2007). It is appropriate therefore to present it in this context and draw analogies with the thesis.

In statistical experiment design, a *factor* is an independent variable that influences the response of a particular system. To draw analogy with the design of engineering systems, a factor can be regarded as a particular design element or management decision rule with several possible values, known as *levels*. Taking the example of an electric-powered aircraft from (Frey and Wang, 2006), a factor influencing duration of flight, which is the measured system's response, can be wing surface area. As shown in Table 3.1, this factor is assumed to take on two level values according to this particular design requirement: 450 in^2 and 600 in^2. Table 3.1 also shows other examples of factors influencing the aircraft's duration of flight.

Table 3.1: Examples of factors involving design elements in the case of an electric-powered aircraft (Frey and Wang, 2006). For example, the factor "wing area" is assumed to have two levels: 450 in^2 (denoted as –) and 600 in^2 (denoted as +).

Factors	*Level*	
	–	+
Propeller diameter	7 in.	8 in.
Propeller pitch	4 in.	5 in.
Gear ratio	1:1	1:1.85
Wing area	450 in.^{2}	600 in.^{2}
Cells in battery	7	8
Motor type	SP400 7.2V	SP480 7.2V
Number of motors	1	2

Factors can contribute in two ways to the response of a given system: through main factor effects and interaction effects between the factors. A factor that affects the response of the system consistently throughout all experimental measurements is said to contribute a main factor effect to the response. A factor whose contribution to the measured signal changes when it is used in combination with other factors is said to contribute interaction effects to the measured signal.

This reality is depicted in the equation below. In this equation, y is the measured system output, which is a function of the different factors x_i influencing the response. The coefficients β_i represent the contribution from each factor's main effect on the measured response, β_{ij} represent contributions from the interaction effect between factors x_i and x_j, and ε_k is the measured experimental error. For two-level factors, x_i can take values two values $\{+1, -1\}$.

$$y(x_1, x_2, \ldots, x_n) = \sum_{i=1}^{n} \beta_i x_i + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \beta_{ij} x_i x_j + \varepsilon_k$$

Therefore, the measured response of a system can be characterized by the sum of the effects of the main and interacting factors. What needs to be done to describe such response fully in the form of this equation is to determine a set of possible factors, and run several experiments measuring the response under all possible combination of factor levels. In the statistical experiment design jargon, this is known as performing a full factorial analysis of the system. Ideally, this is what designers would hope to achieve in step 4 of the analysis methodology to find the combination of design elements and management decision rules that provides the best response of the system.

In reality however, designers seldom have time to perform a full factorial analysis to get a statistically significant description of the response of the system. This is precisely the kind of situation addressed in this thesis. Here, searching the combinatorial space amounts to finding a good combination of design elements and management decision rules affecting the value and performance of the system. The goal is to find the most relevant catalog of operating plans while avoiding a complete factorial analysis.

3.3.1 Reducing the Number of Experiments

Several methods exist in the statistical experiment design literature to reduce the number of experiments necessary for factorial analysis. Two of them are presented in this section: fractional factorial analysis and adaptive OFAT. The section starts from a hypothetical example of statistical experiment design for full factorial analysis. It follows with concrete examples of application of fractional factorial analysis and the search algorithm adaptive OFAT to find the best response of the hypothetical system. These search methods both require fewer experiments than full factorial analysis.

Figure 3.3 shows graphically an example of statistical experiment design for full factorial analysis. This particular design has three factors *A*, *B*, and *C* with two levels for each factor (+ and –). Table 3.2 shows measurements obtained from a set of eight hypothetical experiments. Each experiment represents one measurement of the response on the hypothetical system given a particular combination of factor levels.

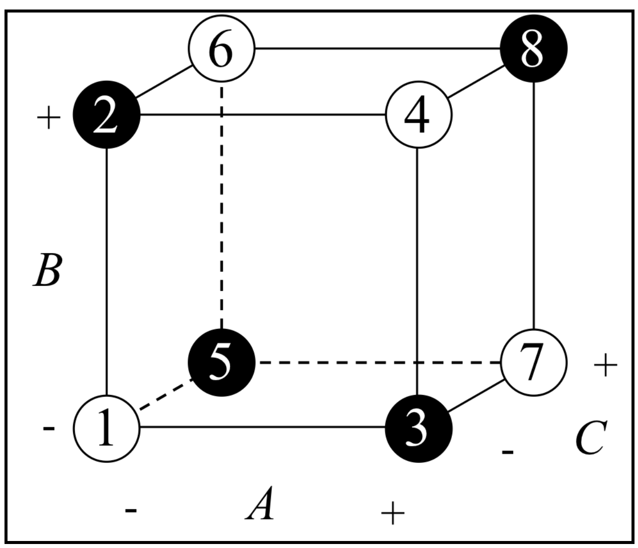


Figure 3.3: Representation of a statistical experiment design for full factorial analysis. This design involves three factors (*A*, *B*, and *C*) with two levels each (+, –), as inspired from example in (NIST/SEMATECH, 2006).

Table 3.2: Hypothetical measurements obtained by performing the experiments presented in the design of Figure 3.3, as inspired from (NIST/SEMATECH, 2006).

Experiment number	A	B	C	System's response
1	–	–	–	33
2	–	+	–	41
3	+	–	–	63
4	+	+	–	57
5	–	–	+	57
6	–	+	+	59
7	+	–	+	51
8	+	+	+	53

3.3.1.1 Fractional Factorial Analysis

In the case of fractional factorial analysis, all possible combinations of factor levels are listed as in Table 3.2, but only a subset of combinations is selected to perform experiments and measure the system's response.

In this kind of analysis, the selected subsets of experiments should ideally be both balanced and orthogonal (NIST/SEMATECH, 2006). A balanced experimental design is one where the number of experiments is the same for each combination of factor levels. Assuming the response of the system from which measurements are taken can be modeled using the linear equation above, an experiment design is orthogonal if estimates of all parameters are uncorrelated (Kuhfeld et al., 1994). This means each parameter estimate has to be independent from other estimates in the model. In practice however, it is very difficult to find perfectly orthogonal designs, and most practitioners rely on non-orthogonal experiment designs (Kuhfeld et al., 1994).

In this design, all factor level combinations are depicted by experiments 1 to 8. Since one measurement is made for each combination, the design is balanced. For simplicity and illustrative purpose only, it is assumed that the correlation between the model parameters is 0. Therefore the design can be considered orthogonal.

Given this, the dark and light dots on Figure 3.3 represent two balanced and orthogonal subsets of four experiments that can be used for fractional analysis. The "white" subset consists of experiments 1, 4, 6, and 7, while the "black" subset consists of experiments 2, 3, 5, and 8.

If designers are interested in finding the maximum response of the system using fractional factorial analysis, they can perform "white" experiments 1, 4, 6, and 7, and retain the combination of factor levels that provides the highest response of the system. In this case, the highest system's response is 59, provided by the combination (A: –, B: +, C: +). Alternatively, they can perform the "black" experiments 2, 3, 5, and 8, and obtain a best response of 63 with a combination of factor levels (A: +, B: –, C: –).

The advantage of using fractional factorial analysis is that instead of performing eight experiments, designers only need to perform four, which in this case represents 50% of the total number of experiments. The disadvantage is that depending on the subset selected, the combinations of factor levels (equivalent to a certain design choice in analogy with engineering system design) may not be the same.

3.3.1.2 Adaptive OFAT

Another search algorithm introduced by Frey and Wang (2006) reduces the number of experiments in factorial analysis. This algorithm, known as adaptive OFAT, has two versions: one for cases where factor levels are discrete and one where they are continuous. The discrete case is presented first.

In a space where n is the number of factors and where each factor has two levels, adaptive OFAT reduces the number of experiments from 2^n to $n + 1$. The adaptive OFAT search algorithm is useful in this methodology because it reduces both computational efforts and time devoted to searching the combinatorial space. It also guides the search for factors that most influence the response of the system.

The search algorithm is presented in Figure 3.4. The same three factors as above (*A*, *B*, and *C*) have influence on the response of the system, and each factor has two levels (+ and –). The algorithm starts with a baseline combination of factor levels (*A*: –, *B*: +, *C*: +) as shown on Figure 3.4), an experiment is done, and a measurement is taken given that particular combination. This initial combination, called *baseline experiment*, is either selected randomly to offer greater generality or through a preferred choice from designers. The sequence in which factors are investigated subsequently should also be generated randomly (Wang, 2007).

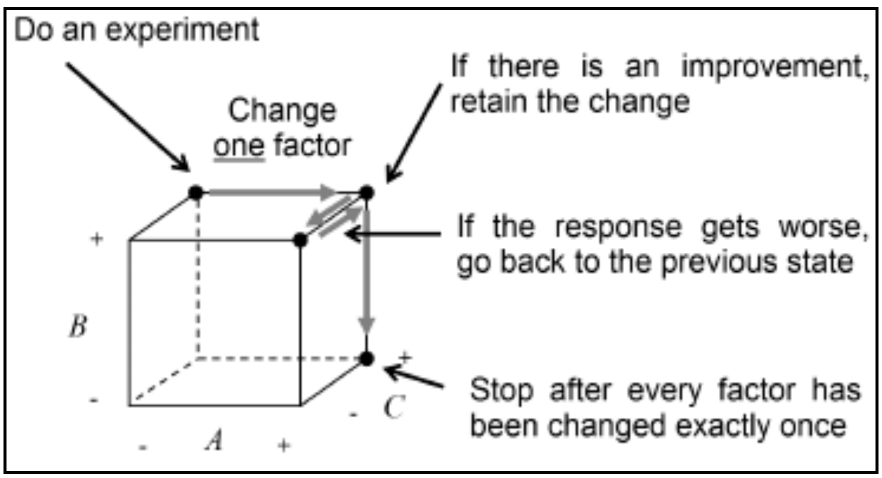


Figure 3.4: Adaptive OFAT as applied to a system with three two-level factors (*A*, *B*, and *C*). (Source: Frey and Wang, 2006).

One factor level is then modified. If the system's response is improved, the change is kept. If not, designers go back to the previous combination of factor levels. The process is repeated until all factors are changed at least once, which means $n + 1$ experiments are performed, including the baseline experiment. Hence, only a fraction $(n + 1) / 2^n$ of the combinatorial space is explored. For instance, if three factors are responsible for the response of the system as in the previous example, $n = 3$ and $2^3 = 8$ possible combinations exist. The search algorithm therefore explores 4/8 = 50% of the combinatorial space, similar to the fractional case. As n increases, the percentage of combinatorial space explored by the algorithm steadily decreases, which is the interesting feature of adaptive OFAT.

The adaptive OFAT algorithm is applied to the experimental design shown in Figure 3.3 using experimental data from Table 3.2. For more generality, the baseline experiment is selected randomly, together with the sequence in which the factors are investigated. The randomly generated baseline experiment is (*A*: –, *B*: –, *C*: –), and the sequence is *A* followed by *B* followed by *C*.

The measured response of the system for the baseline experiment is 33. Changing factor *A* to its positive level (+), the measured response for the combination of factor levels (*A*: +, *B*: –, *C*: –) is 63. The change is retained because there is clear improvement over the previous response of the system. Factor *B* level is then changed to positive (+), and the measured response for the combination of factor levels (*A*: +, *B*: +, *C*: –) is 57. This combination is not retained because it gives a lower response than the previous one, and so the previous combination (*A*: +, *B*: –, *C*: –) is retained. The final experiment changes factor *C* level to positive (+), and the measured response for the combination (*A*: +, *B*: –, *C*: +) is 51, which again is lower than the response of 63 obtained with (*A*: +, *B*: –, *C*: –). Therefore, the best combination of factor levels for the system using adaptive OFAT is (*A*: +, *B*: –, *C*: –) with a corresponding response of 63.

In this particular case, the adaptive OFAT algorithm performs as well as the fractional factorial method if designers correctly select the "black" subset of experiments. This result is however greatly dependent on the choice of baseline experiment, and on the sequence in which the factors are investigated. For example, the interested reader can check that if the baseline experiment is (*A*: –, *B*: +, *C*: +) with the same sequence of investigation (*A* followed by *B* followed by *C)*, the measured output is 59, and the best combination of factor levels is that of the baseline experiment (*A*: –, *B*: +, *C*: +). This is equivalent to selecting the "white" subset of experiments in fractional factorial analysis.

3.3.1.3 Continuous Version of Adaptive OFAT

Another version of adaptive OFAT exists for factors and levels that are continuous (Wang, 2007). This method provides better assurance that no local maximum is selected when applying the algorithm at the expense of a global maximum. The approach however works with a representation of the system's response in the form of the equation above describing a system's output. It aims at updating one step at a time the coefficients β_i, described as continuous probability distributions, and based on the maximum system's response obtained through each experiment.

3.3.2 Choosing to Use Adaptive OFAT

Frey and Wang (2006) as well as Wang (2007) suggest using adaptive OFAT for guiding the search for the best elements in engineering system design, but not necessarily in a manner that considers flexibility nor managerial issues. In this thesis, the application of adaptive OFAT is extended to searching the combinatorial space while considering flexibility as part of the evolution of both design and management processes.

As illustrated before, one problem with adaptive OFAT is that no guarantee exists that a global maximum will be found. Depending on the baseline experiment selected and the sequence in which combinations of design elements and management decision rules are investigated, it is possible that a local maximum is found instead of a global one. This is why for greater generality, it is recommended to generate randomly the sequence of investigated factors and baseline experiment (Wang, 2007).

Regarding the choice between discrete and continuous adaptive OFAT, this thesis argues that the continuous version makes the analysis overly complex for engineering system design and management. Briefly stated, this complexity is introduced by the fact that factors x_i and coefficients β need to be described and considered as probability distributions with means and standard deviations being updated by the continuous version of the algorithm.

It is unlikely that designers and program managers will be interested in adding an extra layer of complexity introduced by the continuous version of adaptive OFAT, even though it is theoretically more appealing. It is a basic premise of this work that they have very little time, financial, and computational resources to devote to modeling and simulations. In addition, project valuation and assessment of flexibility needs to be done in a clear, understandable, and transparent manner. This is why the discrete version of adaptive OFAT is recommended.

Considering the above, using discrete adaptive OFAT is recommended in this thesis because it is easy to use, implement, and because it structures the search for the best combination of design elements and management decision rules to build the catalog of operating plans. Its effectiveness over fractional factorial analysis is demonstrated in (Frey and Wang, 2006; Wang, 2007), and it has the conceptual advantage of being Bayesian and thus easily responsive to a priori knowledge about the system. The choice for which experiments and combination of factors should be kept is made intrinsically part of the algorithm, thus simplifying this task for designers. This is especially useful when designers have limited intuition on which combination produces best results. Considering this, if good intuition is available on which combinations should be explored and those that should not, designers should obviously integrate this knowledge as part of the analysis methodology.

3.4 Assessing the Value of the Catalog of Operating Plans

Once sources of flexibility are identified in step 3 and the catalog of operating plans is created in step 4, it is interesting to determine how much value the catalog approach adds compared to an inflexible design that uses only one inflexible operating plan.

The analytical tool recommended in this thesis to assess the value of the catalog of operating plans uses Monte Carlo simulations. The advantage of the method is to use tools and software (like Excel®) familiar to most designers, which does not require the introduction of new software and optimization techniques. The method is transparent and depicts reality in a financial language familiar to most managers and financial officers (e.g. pro forma income statement). It can simulate as many uncertain variables as computational power allows and as relevant for the search for the best catalog of operating plans. It is also possible to implement different management decision rules that are inherent part of the catalog.

To the contrary of the method based on binomial trees pioneered by (Cox et al., 1979) to assess the value of real options, simulations do not make use of the concept of arbitrage enforced pricing to justify the use of a risk-free discount rate. Therefore, some analysts may complain about the theoretical validity of Monte Carlo simulations. On the other hand, simulations are much easier to understand and implement than binomial trees because they do not require a detailed understanding of many options-related concepts like arbitrage enforced pricing. They are also a lot more intuitive.

The method to value the catalog of operating plans is derived from the one de Neufville et al. (2006) presented to assess the value of flexibility in engineering systems. It uses the same example of development of a parking garage introduced in Section 3.2, where demand for parking space is the uncertain variable giving rise to uncertain revenues.

The general process for valuing the catalog involves three parts. The first requires the model built in step 1 of the analysis methodology that is inflexible both in terms of design and management decision rules. This model therefore shows only one operating plan. It can take the form of a pro forma income statement as shown in Figure 3.5, typical of financial analyses performed in the industrial world.

Uncertainty is then recognized in the model by simulating many scenarios of the uncertain variable (e.g. two thousand) to see how they each affect the project valuation metric, in this case NPV. This step incorporates many fluctuations around the analyst's original deterministic projections of demand from step 1. These fluctuations reproduce assumed probability distributions around the analyst's demand projection for each year. One simulation depicting one demand scenario for the entire project duration is shown in Figure 3.1.

Year	0	1	2	3
Demand		750	893	1015
Capacity	0	800	800	800
Revenue	$0	$7,500,000	$8,000,000	$8,000,000
Operating costs	$0	$1,600,000	$1,600,000	$1,600,000
Land leasing and fixed costs	$3,600,000	$3,600,000	$3,600,000	$3,600,000
Cashflow	$0	$2,300,000	$2,800,000	$2,800,000
DCF		$2,053,571	$2,232,143	$1,992,985
Present value of cashflow	$18,623,992			
Capacity cost for up to two levels	$6,400,000			
Capacity costs for levels above 2	$7,392,000			
Net present value	$1,231,992			

Figure 3.5: Example of pro forma income statement based on deterministic projections of demand for a parking garage.

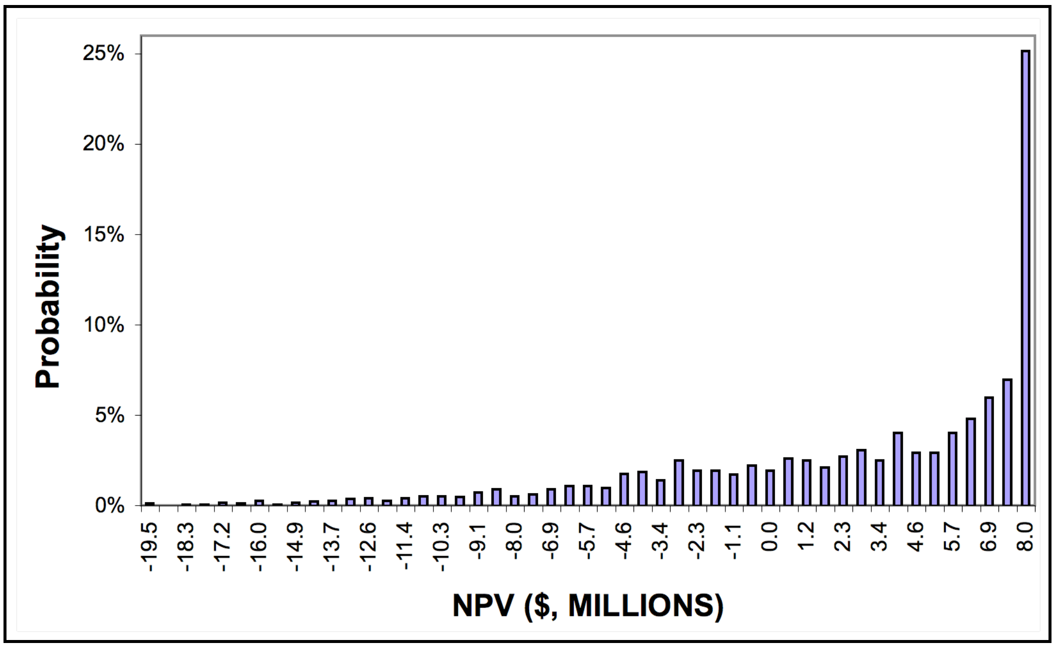


Figure 3.6: Example of histogram distribution resulting from Monte Carlo simulations.

The results of the Monte Carlo simulation can be represented through a histogram (Figure 3.6). Statistical measures then describe the distribution of outcomes, such as mean or Expected NPV (ENPV), standard deviation, minimum and maximum NPV, etc.

In such paradigm, managers now deal with a distribution of possible NPV outcomes instead of one based on deterministic projections. Because of this, it is interesting to introduce another graphical tool helpful for managerial decisions. This is the cumulative distribution function (CDF), or Value At Risk and Gain (VARG) curve, which depicts the cumulative probability of having NPVs below a certain value (Figure 3.7). For instance, this VARG curve shows there is a 10% chance of having NPV values below -\$5M, and a 30% chance of having NPV above \$7.5M.

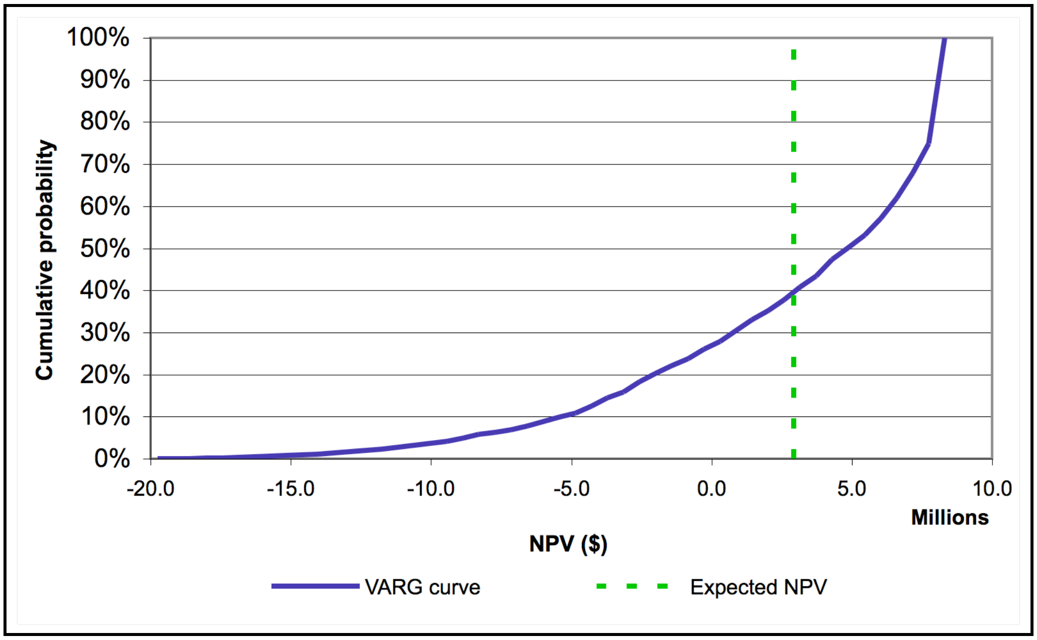


Figure 3.7: Example of VARG curve depicting the range of possible NPV outcome for a particular project. An example of possible ENPV is also shown.

The second part consists of assessing the value of the catalog of operating plans using similar mechanisms. For each simulation of uncertain variable scenarios, an operating plan is selected that is best suited for that particular scenario. In other word, the simulated scenario is assigned to a particular category as discussed in Section 3.2. This simulates program manager's decision to use a particular operating plan given observations of a particular trend in the uncertain demand variable.

For instance, a simulated scenario with low initial value and high percentage growth between first and final years can be associated to one of the few scenarios in step 2 of the methodology because it exhibits a similar behavior. Since the scenario of step 2 is associated to one particular operating plan in step 4, the simulated scenario can be associated by extension to this particular operating plan. Simulations are run once again to find the histogram, VARG curve, and ENPV results from following such managerial behavior.

The third part computes the additional value provided by the catalog of operating plans as follows:

$$E[V_{Catalog}] = ENPV_{Case\ with\ catalog.} - ENPV_{Inflexible\ case}$$

That is, the expected value of a particular catalog of operating plans is found as the difference between the ENPV of the design with a catalog of operating plans and ENPV of the inflexible case.

Following this, Chapter 4 applies the analysis methodology and adaptive OFAT algorithm to two realistic case studies. These demonstrate concretely how the approach suggested in this thesis can be useful in designing and managing engineering systems.

Chapter 4 – Case Studies

This chapter applies the proposed methodology and concepts to two realistic case studies. The goal is to demonstrate by example how this methodology can be applied in reality. The first case study is inspired from the development of a parking garage near the Bluewater commercial center in the United Kingdom. The second relates to the development of a real estate project in the United States. The purpose of using two different case studies is to explore the generality of the approach and highlight some differences in application.

4.1 Bluewater Commercial Center Parking Garage

As presented in (de Neufville et al., 2006), this first case study relates to the construction of a multi-level parking garage to suit the needs of customers at the nearby Bluewater commercial center. Several design questions arise, such as the number of levels that should be built to accommodate demand in parking space. The authors use the case as a pedagogical tool to demonstrate how uncertainty and flexibility can affect design decisions and maximum ENPV when complex systems are designed and managed in the computational way described in Figure 2.3.

Figure 4.1: Example of parking garage. (Source: SARAA, 2007).

The original case makes three important points. First, the value of an investment assuming deterministic projections of the uncertain variable, in this case demand for parking space, typically does not correspond to the realized value of a project. One needs to shift from deterministic "NPV perspective", where one measurement of the value of the system is made, to the perspective of ENPV. Second, design analyses assuming deterministic exogenous effects may provide wrong design decisions. Third, flexibility in design may increase value by capitalizing on unexpected upside opportunities and reducing losses in case of downside events.

In this original case, analysis considering standard pro forma cash flow based on a single future scenario suggests an initial design of six floors with maximum NPV = $6.2M (Figure 4.2). This measure however is necessarily unrealistic because it does not recognize uncertainty. It is not used as a basis for comparison in the analysis that follows in the remainder of Chapter 4.

Recognizing that demand is uncertain (through two thousand Monte Carlo simulations of demand scenarios) changes conclusions to a design with five initial floors as seen on Figure 4.2, and reduces the ENPV by more than half the amount of the deterministic case. The authors then show that incorporating flexibility improves ENPV. This ability to adapt to uncertainty in parking space demand brings the initial number of floors down to four, and nearly doubles the maximum ENPV obtained compared to the inflexible case.

This flexibility takes advantage of possible high demand through the ability to expand the number of floors while limiting this number initially to guard against the possibility of losses. Expansion is possible by incorporating stronger columns in the initial design. This latter design improves the ENPV of the project by reducing initial capital expenditures, and by providing the ability to expand floors and generate more profits.

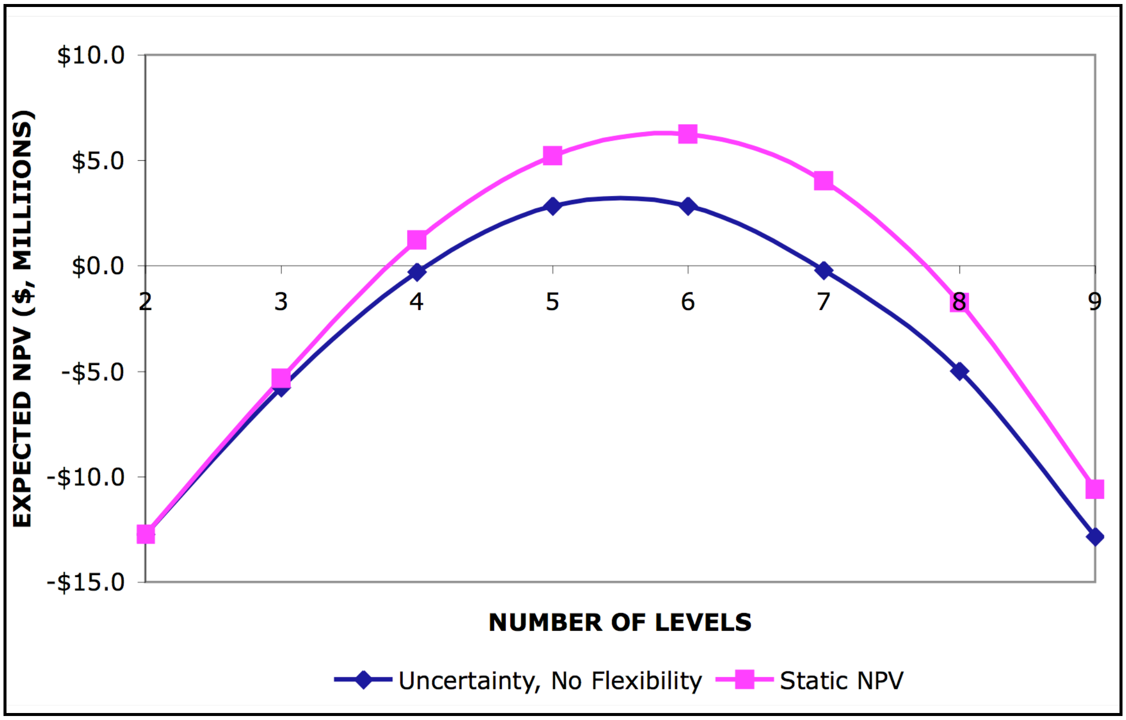


Figure 4.2: Results from varying the number of initial floors in the static case with deterministic projections and recognizing uncertainty through two thousand Monte Carlo simulations.

The authors however consider only one management decision rule, which is to expand by one additional floor after observing demand higher than capacity for two consecutive years. They recognize that flexibility through expansion can add value, but do not focus on the richness of possible combinations of design elements and management decision rules. How would a decision to expand after one or three years affect the value of the system, depending on a certain number of initial floors?

This observation translates into several design elements and management decision rules being ignored that may potentially improve value. Examples can be the number of floors added in each expansion phase, or the number of consecutive years for which demand needs to be higher than capacity in order to expand. Therefore, this thesis proposes to explore the combinatorial space and construct a catalog of operating plans that takes advantage of good combinations of design and management decision rules depending on a limited set of demand scenarios. This approach also limits the amount of computational effort that is required. This is done below through application of the analysis methodology introduced in Chapter 3.

4.1.1 Step 1: Build an initial model of the engineering system to measure value and performance.

In the original case, design is guided by the prospect of making money, and therefore design decisions are driven by NPV (and ENPV when simulations are used). This is the financial metric measuring performance for this particular system. The main uncertain variable is demand for parking space.

The initial model consists of a traditional pro forma discounted cash flow (DCF) Excel® spreadsheet using deterministic projections of parking space demand. The model is developed from the following assumptions (de Neufville et al., 2006):

- The deterministic point forecast is that demand on opening day is for 750 spaces, and rises exponentially at the rate of 750 spaces per decade up to a limit of 1750 spaces;
- The project has duration of twenty years;
- Average annual revenue for each space used is $10,000, and the average annual operating cost for each space available (often more than the spaces used) is $2,000;
- The lease of the land costs $3.6M annually;
- Construction costs $16,000 per space for pre-cast construction, with a 10% increase for every level above ground level;
- The site is large enough to accommodate 200 cars per level; and
- The discount rate is taken to be 12% for the entire project duration.

Figure 4.3 shows an example of pro forma statement for a design with six initial floors while Figure 4.4 shows initial demand projections leading to this assessment. Note in Figure 4.3 that all financial values are given at the end of each year. For example, decision to build occurs at year 0 (now) and requires land leasing and fixed costs of $3.6M, as well as construction costs of

$22.8M. The first 750 parking spaces are ready one year after. Realized demand, revenues, operating costs, land leasing and fixed costs in year 1 and subsequent years are given at the end of each year. Since the duration of the project is twenty years, demand is given twenty times starting at year 1 and finishing at year 20, as shown in Figure 4.4.

Year	0	1	2	3
Demand		750	893	1015
Capacity	0	1200	1200	1200
Revenue	$0	$7,500,000	$8,930,000	$10,150,000
Operating costs	$0	$2,400,000	$2,400,000	$2,400,000
Land leasing and fixed costs	$3,600,000	$3,600,000	$3,600,000	$3,600,000
Cashflow	$0	$1,500,000	$2,930,000	$4,150,000
DCF		$1,339,286	$2,335,778	$2,953,888
Present value of cashflow	$32,574,737			
Capacity cost for up to two levels	$6,400,000			
Capacity costs for levels above 2	$16,336,320			
Net present value	$6,238,417			

Figure 4.3: Example of pro forma statement and DCF model using deterministic projections for parking space demand. Note that only 3 years are shown here out of 20 for the project's duration.

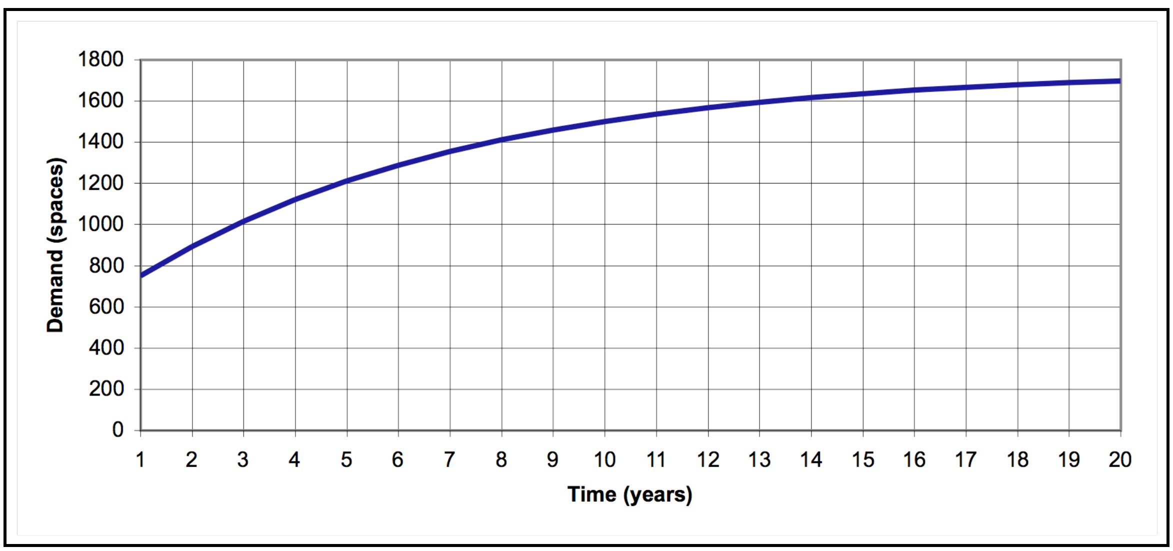


Figure 4.4: Deterministic projection of demand for parking space for the 20-year project duration.

An initial analysis is done based on the assumptions above. The maximum NPV obtained by varying the number of initial floors is \$6.2M, which corresponds to the design with six initial floors. This analysis is referred to as the static case. It corresponds to engineering and management practice when uncertainty is not recognized.

The results from this static analysis however cannot be relied upon because they do not recognize that uncertainty in demand affects the value of the system. They are unrealistic and most likely wrong. The basis for determining whether the analysis methodology improves value is therefore to measure how much value the catalog of operating plans adds to the ENPV of an inflexible design that recognizes uncertainty. In this case, the inflexible design is the one producing the highest ENPV under Monte Carlo simulations. This performance value is measured in step 5. It is the benchmark against which any improvement brought by the analysis methodology is measured.

4.1.2 Step 2: For each source of uncertainty, propose a limited set of uncertain variable scenarios and review initial model.

In this case study, only demand in parking space is considered as a source of uncertainty. In order to find relevant demand scenarios that adequately represent the reality, the method proposed in Section 3.2 should be used.

For simplicity here, the characteristic chosen to produce and categorize scenarios is the percentage growth between the first and fifth years. The motivation for choosing this simple characteristic is to study the effect on the value of the system of rapid demand growth in early years, and to simplify the demonstration of the analysis methodology.

As mentioned in Section 3.2, a more precise way to categorize scenarios can be to look at combinations of low and high initial value and low and high percentage growth between first and final years to create four categories of demand scenarios. This categorization algorithm was not implemented in this thesis. It is left for future work to determine how results would change using this type of categorization characteristics.

The five categories of demand scenarios are listed in Table 4.1. The mid-value on the table is the middle value between two subsequent percentage growth rates. It is used to categorize demand scenarios in step 5. For example, a scenario having percentage growth below 38% in step 5 will be classified as similar to scenario 1, between 68% and 38% as similar to scenario 2, etc.

Figure 4.5 shows the set of five demand scenarios chosen to represent the reality of uncertainty in parking space demand, and to represent each category of scenario described in Table 4.1. These five scenarios are used to create the catalog of operating plans in step 4. As mentioned, an algorithm based on these five categories is implemented in step 5 to classify simulated demand scenarios and assess the ENPV of the catalog of operating plans.

Table 4.1: Percentage growth between first and fifth years for each of the five demand scenarios. The midway mark, or the percentage value between two scenarios, is used in step 5 as a criterion to classify new demand scenarios.

Demand scenario category	Percentage increase from first to fifth year	Mid-value
1	131%	123%
2	115%	100%
3	84%	68%
4	52%	38%
5	24%	

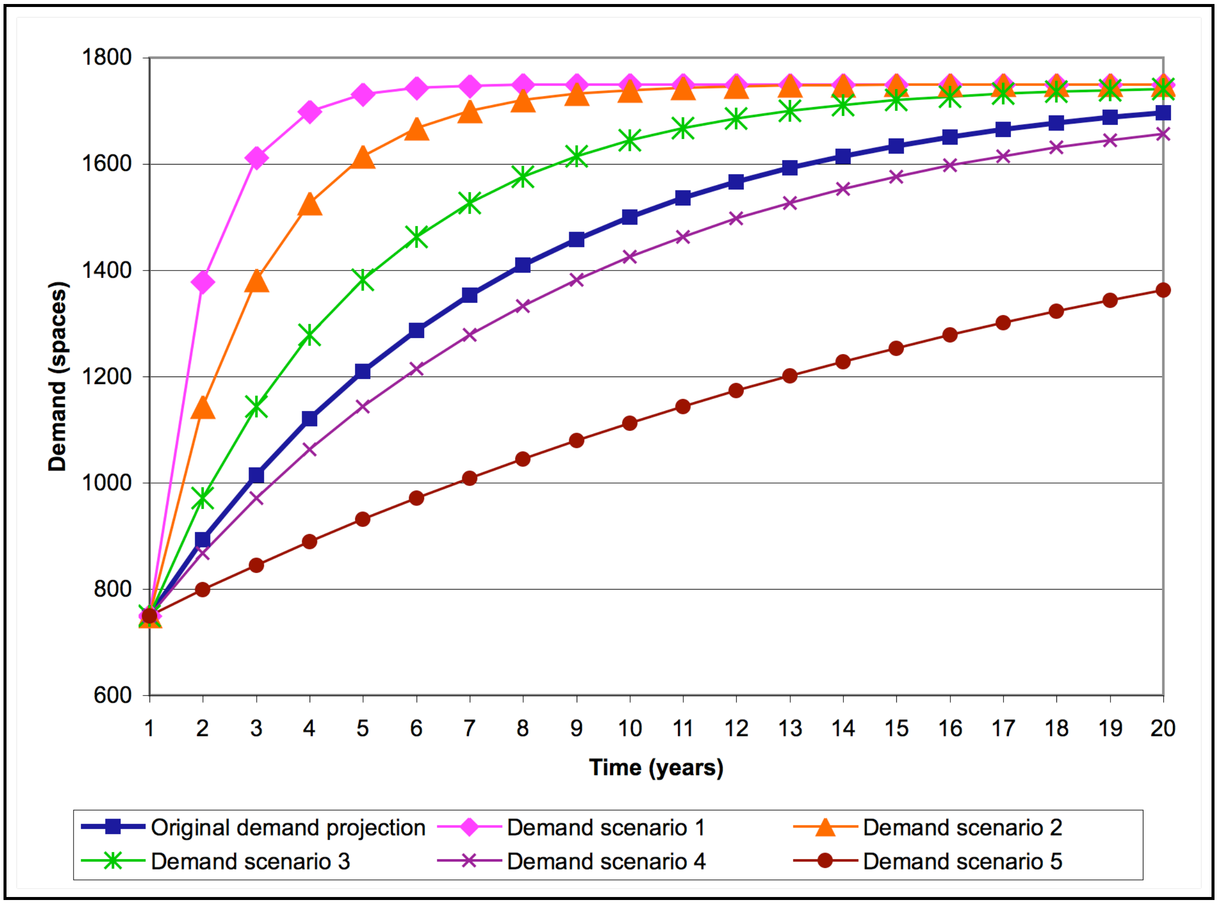


Figure 4.5: Set of five demand scenarios used to build the catalog of operating plans. The original deterministic demand projection is also shown.

4.1.3 Step 3: Determine the main sources of flexibility in the system and incorporate in the model.

As mentioned in Section 2.4, there are typically two areas where program managers can adjust to uncertain variables through flexibility: "in" the system, which includes in the upstream design and system's operations, and "on" the system. In this particular case study, screening for flexibility is done at a relatively superficial level, and only brainstorming sessions are used. For more detailed screening methodologies, the reader is referred to Section 2.4. The following subsections show the output of the brainstorming sessions.

4.1.3.1 Flexibility "In" Design

In the parking garage case, two technical adjustments are done "in" the system to adapt to uncertain demand scenarios presented in step 2. Designers can initially build fewer parking floors, reduce upfront capital investment, and therefore reduce losses if uncertain demand is unfavorable. They can also acquire stronger columns to allow capacity expansion as demand increases to capture additional profits. The real cost of acquiring this flexibility is approximated as 5% of total initial construction costs.

The flexibility to expand takes advantage of demand that is higher than expected in the deterministic projections. The five scenarios showing different demand growth rate will be used to create five operating plans in step 5 that use this flexibility at different levels of intensity. For a scenario where demand increases rapidly, like scenario 1 in Figure 4.5, the emerging operating plan will use the flexibility to capitalize quickly on this good opportunity. For a scenario where demand increases more slowly, like for scenario 5 in Figure 4.5, this flexibility might be exploited less.

Since the flexibility to expand is extremely useful in light of the uncertain demand scenarios selected in step 2, it is incorporated in the Excel® model of the system.

4.1.3.2 Flexibility "In" Operations

At the operations level a parking garage is fairly straightforward. This contrasts with an airline where aircraft routes and destinations can be modified to accommodate fluctuating regional demand. Here, the parking garage is in a fixed location, and it is assumed that clients always use the same parking spot for the entire contract duration. Nevertheless, there are sources of flexibility that can be exploited. For instance, managers may decide to operate the garage annually only ten months out of twelve or vary opening hours.

To incorporate this kind of flexibility in the model, it would be useful to have separate demand scenarios for customers interested in using the garage for a period of ten months instead of twelve, or to use it assuming different opening hours.

Since in this case the only uncertain variable scenarios are demand for parking space, irrespective of time and opening hours, this flexibility is difficult to incorporate in the model. For brevity it is left aside from this analysis, but could be considered as part of a more detailed study.

4.1.3.3 Flexibility "On" Project

For adjustments "on" project, program managers have the ability to close the project if demand is lower than capacity for a certain number of years, thus reducing the maximum amount of losses. It is also possible to delay initial capital investment to gather information about market demand.

The last set of flexibility "on" project is to adjust parking space price. In commodity industries with no monopoly like the copper industry, firms are price takers due to free market pressures. Therefore, commodity price patterns need to be considered as an uncertain variable uncontrollable by managers.

In the parking garage case, the annual leasing price for parking space does not fluctuate as copper price does on the London Metal Exchange. Managers have control over the price they set, which depends on location, luxury level, quality of service, etc. In this case, management sets annual price per parking space. It is possible however to change this price depending on demand and market conditions, which is another potential source of flexibility.

In light of the demand scenarios selected in step 2, the above sources of flexibility "on" project could be incorporated in the Excel® model. To simplify the analysis however, the only flexibility considered is the ability to expand.

4.1.3.4 Modifying the Model to Incorporate Flexibility

A large number of design and management decision rules can be incorporated in the Excel® model to simulate flexibility in face of uncertain demand. Only the flexibility to expand is considered here, and only a subset of possible values is chosen for each design element and management decision rules to facilitate the adaptive OFAT search in the next step. Nevertheless, the same analysis can be performed with all sources of flexibility mentioned in the previous section.

The number of initial floors is the first design element incorporated in the model to accommodate a flexible design with stronger columns. It is already implemented in the model since it is used in the deterministic valuation to determine the highest NPV. The number of initial floors is limited to four, five, and six floors for the OFAT search, and because analysis of the static case as done in (de Neufville et al., 2006) shows that the highest NPVs are generated among these values.

At the managerial level, the model allows decisions to expand after two, three, and four consecutive years of demand higher than capacity. Another management decision rule is the number of floors by which to expand, set to one, two, and three floors at a time. Finally, program managers may decide on purpose not to expand in certain parts of the 20-year project duration to study market conditions or avoid useless expansion phases. Hence, decision not to expand in years 1-4 is allowed in the model to study market demand, years 9-12 to study midlife market conditions, and in years 17-20 to avoid useless expansion before the end of the project's lifecycle.

These design and management decision rules are summarized in Figure 4.6. For each design and management decision rule, the possible values, or *levels*, are described by the signs "–", "o", and "+". In the next step, the adaptive OFAT algorithm is applied to find the best combination of design and management decision rules under each of the five demand scenarios found in step 2.

Design Elements and Management Decision Rules	Description	Levels -	o	+
A	Expansion allowed in years 1-4	No	N/A	Yes
B	Expansion allowed in years 9-12	No	N/A	Yes
C	Expansion allowed in years 17-20	No	N/A	Yes
D	Expansion decision rule (years)	2	3	4
E	Number of floors expanded by	1	2	3
F	Number of initial floors	4	5	6

Figure 4.6: Design elements and management decision rules implemented in the model to represent the flexibility to expand the number of floors. The levels represent the different values that can be taken by each design element or management decision rule.

4.1.4 Step 4: Search the combinatorial space and create the catalog of operating plans.

In this case, an operating plan is chosen as the combination of levels, under one of the five demand scenarios, that produces the highest NPV. Adaptive OFAT is used to explore the combinatorial space in search for that particular combination. For each demand scenario, a baseline experiment is chosen and the exploration sequence is determined randomly. One example application of the complete adaptive OFAT to the first demand scenario is shown here. This determines the first operating plan in the catalog of five. The demand scenario under study is shown in Figure 4.7 together with initial deterministic demand projection to get a feel for this proposed growth rate. The same analysis for the remaining four scenarios is shown in the Appendix section.

In this case study, the baseline experiment is chosen by designers to be the same for all demand scenarios under study. It could have been generated randomly for each demand scenario to offer greater generality as suggested by (Wang, 2007). The reason for using the same baseline experiment here is to illustrate the possibility that designers may want to choose it based on their own judgment. The same analysis is performed using randomly generated baseline experiments and OFAT sequences, with results shown in the Appendix section. The next case study on real estate development also generates the baseline experiment randomly for each scenario.

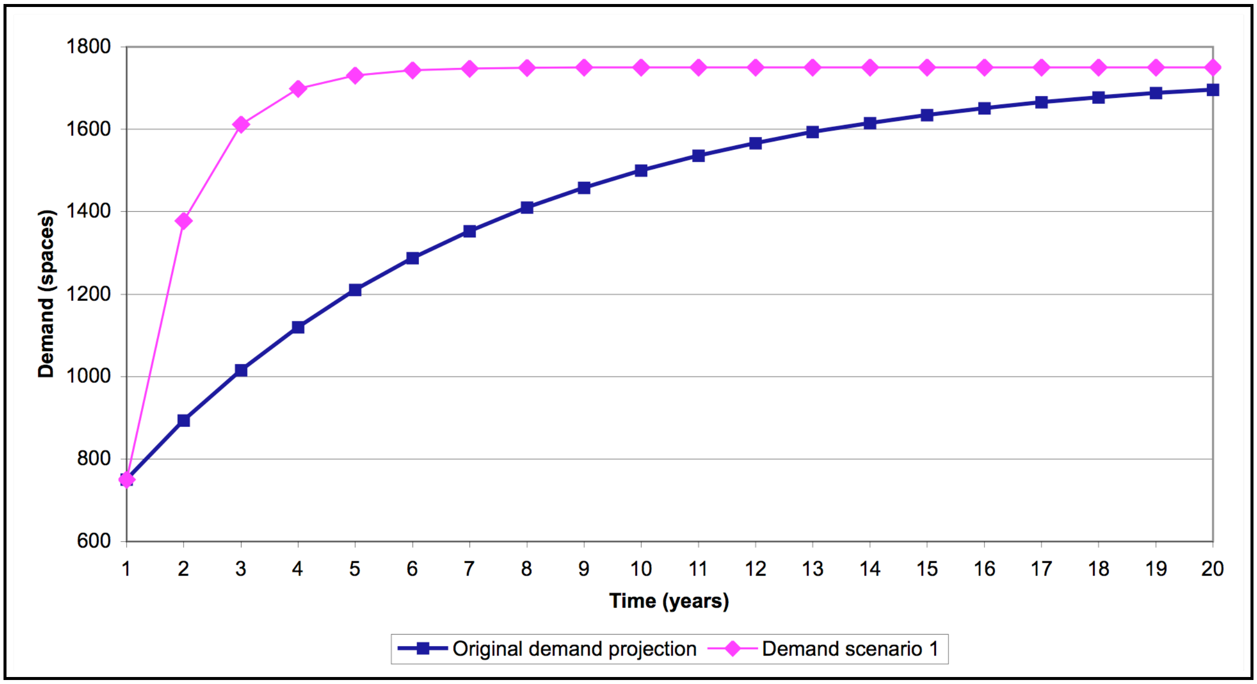


Figure 4.7: Demand scenario 1 is used in this example application of the adaptive OFAT process.

Here, designers want a baseline experiment that exploits well the benefit of the flexibility to expand. They choose it so expansion is allowed in all years (management decision rules A, B, and C all set to "Yes"). Their choice is also to expand when demand is higher than capacity for two consecutive years, to do it one floor at a time, and to start with an initial design with five floors. The sequence in which each design elements and management decision rules are investigated is generated randomly. This information is summarized in Table 4.2. Examples of results obtained with different baseline experiments and OFAT sequences are shown in the Appendix section.

Table 4.2: Baseline experiment and OFAT sequence used to explore the combinatorial space for demand scenario 1. "DE" is the acronym for design element, while "DR" is the acronym for decision rule.

DEs and Management DRs	Description	Baseline Experiment	OFAT Sequence
A	Expansion allowed in years 1-4	Yes	F
B	Expansion allowed in years 9-12	Yes	C
C	Expansion allowed in years 17-20	Yes	E
D	Expansion decision rule (years)	2	D
E	Number of floors expanded by	1	B
F	Number of initial floors	5	A

The adaptive OFAT process is applied as shown in Figure 4.8. Each experiment is performed in order, and the resulting information is shown in each row. The column "DE and Management DR changed" represents the design element or management decision that is investigated for that particular experiment. The column "Level changed to:" refers to the level that is explored in this particular experiment since it is changed from the previous step. For example, in Figure 4.8, experiment 1 starts with the baseline experiment described in Table 4.2. In experiment 2, the first design element explored is F (number of initial floors), and the level is changed from 5 initial floors in the baseline experiment to 4 initial floors in experiment 2. In experiment 3, it is further changed to 6 initial floors.

For each experiment, the measured NPV output is shown, the best overall output is shown in the column "Best output before step", and designers keep the change if there is improvement in the measured response of the system.

Experiment	DE and Management DR changed	Level changed to:	Output = NPV	Best output before step	Keep change?
1 (baseline)			$ 13.4		
2	F	4	$ 10.9	$ 13.4	No
3	F	6	$ 15.1	$ 13.4	Yes
4	C	No	$ 15.1	$ 15.1	No
5	E	2	$ 15.8	$ 15.1	Yes
6	E	3	$ 15.7	$ 15.8	No
7	D	3	$ 14.6	$ 15.8	No
8	D	4	$ 13.5	$ 15.8	No
9	B	No	$ 15.8	$ 15.8	No
10	A	No	$ 13.5	$ 15.8	No

Figure 4.8: Adaptive OFAT process exploring the combinatorial space for the best combination of levels under demand scenario 1. Dollar figures are in millions.

The first operating plan of the catalog is shown in Table 4.3. This is the one that produces the highest NPV under demand scenario 1.

Table 4.3: Best operating plan selected for demand scenario 1.

DEs and Management DRs	Description	Best Operating Plan for Scenario 1
A	Expansion allowed in years 1-4	Yes
B	Expansion allowed in years 9-12	Yes
C	Expansion allowed in years 17-20	Yes
D	Expansion decision rule (years)	2
E	Number of floors expanded by	2
F	Number of initial floors	6

The same search algorithm is applied to the four remaining demand scenarios in Figure 4.5. This analysis leads to the catalog of five operating plans summarized in Table 4.4 and used in step 5.

Table 4.4: Catalog of operating plans obtained from the analysis of five demand scenarios under the adaptive OFAT algorithm. Each plan is associated to its corresponding demand scenario in Figure 4.5. "DE" means design element, and "DR" means decision rule.

DEs and Management DRs	Description	Op. Plan 1	Op. Plan 2	Op. Plan 3	Op. Plan 4	Op. Plan 5
A	Expansion allowed in years 1-4	Yes	Yes	Yes	Yes	Yes
B	Expansion allowed in years 9-12	Yes	Yes	No	Yes	Yes
C	Expansion allowed in years 17-20	Yes	Yes	Yes	Yes	Yes
D	Expansion decision rule (years)	2	2	2	2	4
E	Number of floors expanded by	2	3	3	1	1
F	Number of initial floors	6	5	5	4	4

4.1.5 Step 5: Assess the Value of the Catalog of Operating Plans

The catalog of operating plans is now tested under a large set of demand scenarios to determine whether it brings improvement compared to an inflexible design. This initial design can be interpreted as using only one inflexible operating plan, and therefore does not explore the additional richness provided by a catalog of five operating plans. This inflexible design is also tested under the same scenarios to find an ENPV as the basis for comparison.

Two thousand Monte Carlo simulations are created where each simulation produces one demand scenario over the 20 years project duration. Figure 4.9 shows an example of simulated demand scenario compared to deterministic demand projection. Volatility around annual demand growth is 15% and uncertainty around initial demand can be 50% off-projections. Annual demand growth for each year is sampled here from a uniform probability distribution.

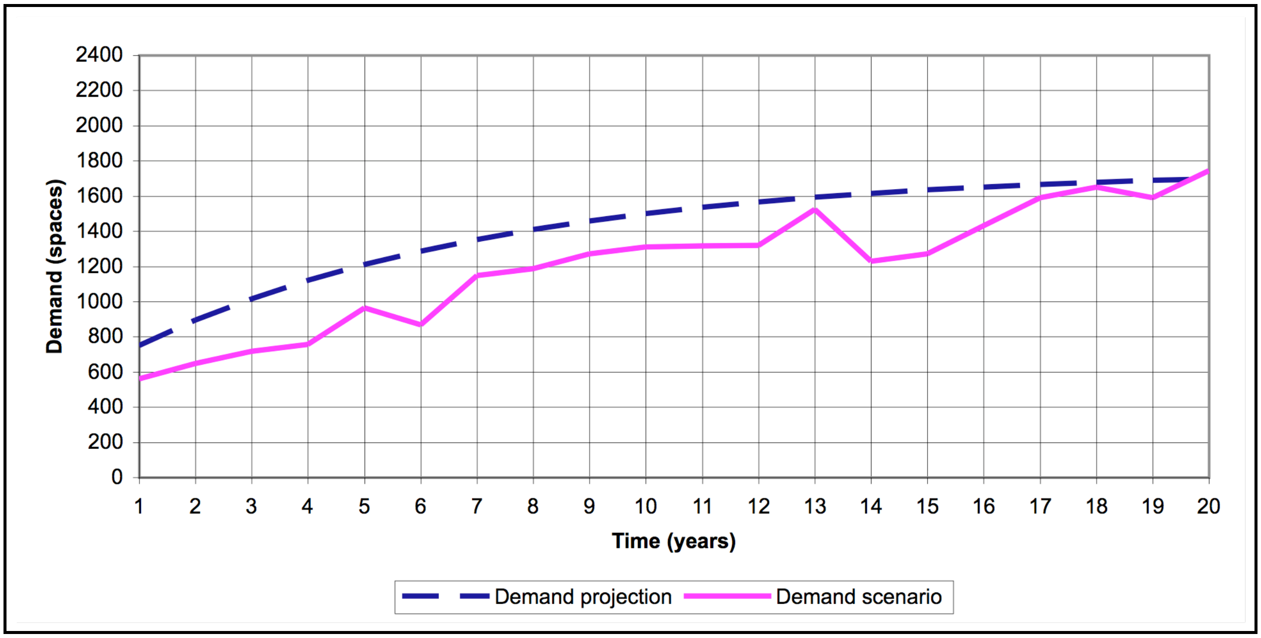


Figure 4.9: Example of simulation of the uncertain demand variable around projected trend for the parking garage example.

Each of the two thousand simulations is associated with one of the five demand scenarios of Figure 4.5, and assigned the corresponding operating plan of Table 4.4. The criterion used to classify each demand scenario is the mid-value percentage growth between two subsequent years for the period between years one and five. Looking at Table 4.1, if demand growth between years one and five is higher than 123% for a particular demand scenario, it is assigned operating plan 1. If it is between 100% and 123%, it is assigned operating plan 2, and so on for all five categories of demand scenarios.

Doing this for two thousand Monte Carlo simulations provides an ENPV for the catalog of operating plans. It also provides other interesting valuation attributes that can be compared to those obtained with the inflexible design. Figure 4.10 shows how many simulated demand scenarios are assigned to each operating plan.

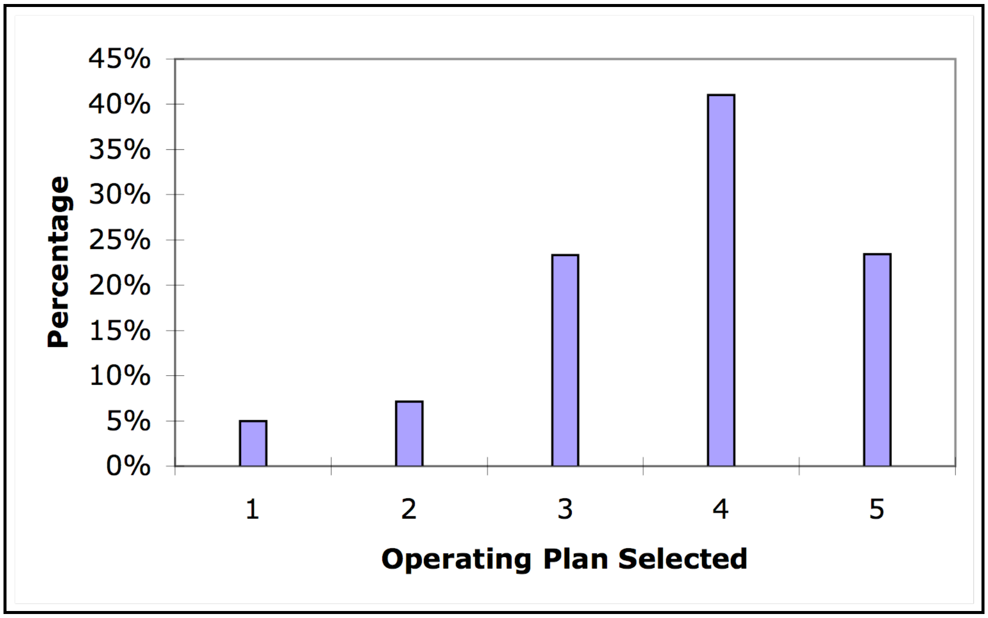


Figure 4.10: Percentage of simulated demand scenarios categorized as one of the five operating plans for the two thousand scenario simulations. Each simulated demand scenario is associated to one operating plan.

Table 4.5 summarizes the results from these experiments. An inflexible parking garage design with five initial floors produces the highest ENPV of \$2.9M when uncertainty is recognized as shown in Figure 4.2. This is similar to the results published by (de Neufville et al., 2006). When each of the simulated demand scenarios is assigned one of the five operating plans described in Table 4.4, the ENPV is \$4.2M.

This latter figure considers the possibility to change the number of initial floors, expansion decision rules, and other management rules by selecting a particular operating plan within the first five years of project life. The operating plan is chosen by observation of demand, and by associating this observation to a particular operating plan. The expected value obtained by considering a catalog of five flexible operating plans over an inflexible design is estimated as \$4.2M – \$2.9M = \$1.3M. It accounts for flexibility in both design and management of the system, and in the fact that program managers can "pick" an operating plan depending on observed demand. The best design decision now depends on observed demand at the time of investment and on the operating plan that is chosen.

As seen on Table 4.5 and the VARG curve on Figure 4.11, many attributes of the distribution of NPV outcomes are improved when the catalog of operating plans is used. The expected initial investment at time zero is lower by about $1.8M, the minimum NPV is higher by $0.7M, and the maximum NPV is higher by $12.2M. Note that the VARG curve shown on Figure 4.11 for the inflexible case provides similar results as published by (de Neufville et al., 2006).

Table 4.5: Summary of results comparing valuation attributes between an inflexible parking garage design with five initial floors, and a flexible design with a catalog of five operating plans. In the latter case, each of the two thousand Monte Carlo simulations are categorized and assigned one of five operating plans.

	Inflexible Design	Flexible Design with Catalog of Operating Plans	Which is Better?
Expected initial investment	$ 18.1	$ 16.3	Flex. and Catalog Better
Expected NPV	$ 2.9	$ 4.9	Flex. and Catalog Better
Expected NPV minus expected cost of flexibility	$ 2.9	$ 4.2	Flex. and Catalog Better
Minimum NPV	$ -19.5	$ -18.8	Flex. and Catalog Better
Maximum NPV	$ 8.3	$ 20.5	Flex. and Catalog Better
Value of catalog of flexible operating plans	$ 0.0	$ 1.3	

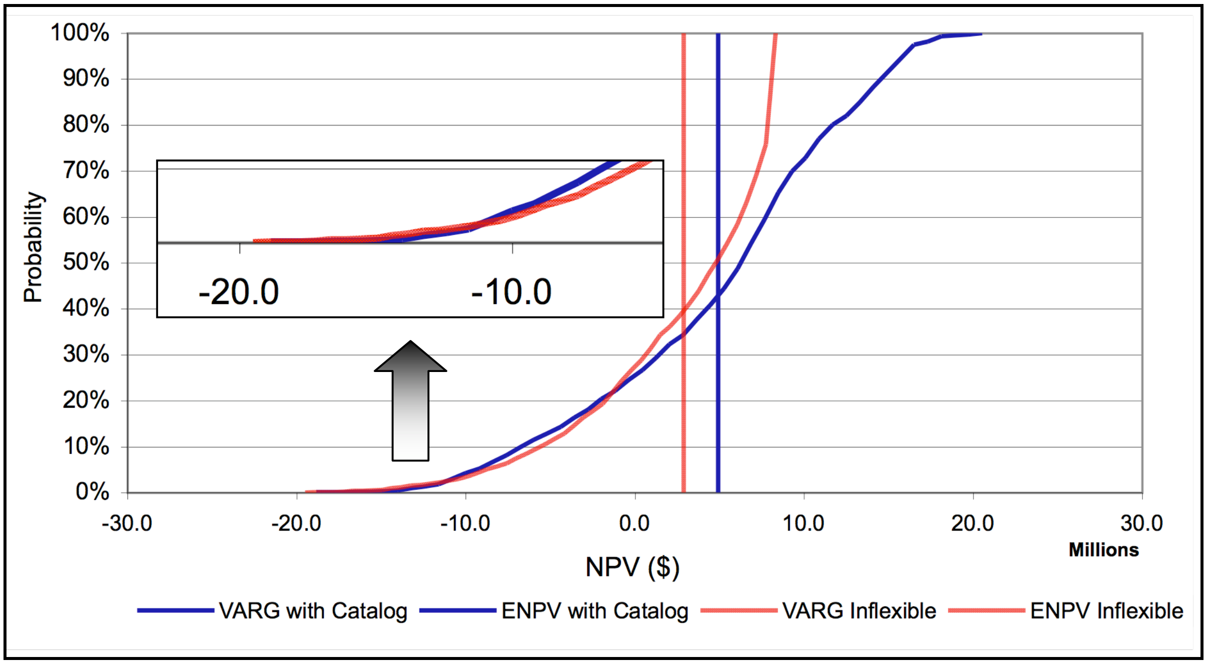


Figure 4.11: VARG curves resulting from Monte Carlo simulations for both the inflexible parking garage design with five initial floors, and flexible design using a catalog of five operating plans. ENPVs for both cases are also shown. The close up on the lower left portion of the figure shows improvement in minimum NPV obtained when a catalog of operating plans is used. The light line finishes just slightly to the left of the dark line, showing a minimum NPV lower for the inflexible case than with the catalog of operating plans.

4.2 Apartment Development Project in the United States

This case is about the development of five phases of apartment units inspired from a real estate development project in the United States by Jones Lang Lasalle (2007). It consists of 430,000 square feet (SF) of apartment units accompanied by relevant infrastructure (site grading, paving, utilities, and landscaping). Each apartment unit has a surface area of 1,000 SF. An interesting feature of this project is that phases are developed around a park having an area of 200,000 SF (about 4.6 acres). Project developers count on this particular feature to attract more potential buyers and increase market value.

Figure 4.12: Artistic view of the proposed apartment development project. (Source: Jones Lang Lasalle, 2007).

The proposal is to develop all five phases, infrastructures, and park in a row between 2007 and 2013 to benefit from economies of scale and reduce costs. Each construction phase takes up to 24 months, and may start one year after the other. The park and infrastructure are constructed along with each phase. Phase II starts one year after the beginning of phase I, and so on for subsequent phases. Table 4.6 summarizes the timing of the development project.

Table 4.6: Summary and timing of the real estate development project. APT stands for apartment building.

Phase	Type	SF	Units	Net Acreage	Start	Completion
I	APT	50,000	50	1.15	1/07	1/09
II	APT	80,000	80	1.84	1/08	1/10
III	APT	90,000	90	2.07	1/09	1/11
IV	APT	110,000	110	2.53	1/10	1/12
V	APT	100,000	100	2.30	1/11	1/13
Total		**430,000**	**430**	**9.87**		

The market value of built property, measured in dollars per square foot, is projected to be higher than development costs for the first few years of the project. This assumption implies that developing phases in a row generates the highest NPV, and is therefore adopted as the best strategy for the static case based on deterministic projections of market value and development costs.

The analysis methodology is applied to this case study to search for a catalog of operating plans that improves value compared to the development plan shown in Table 4.6 that recognizes uncertainty. Uncertainty is recognized and incorporated in the model under two thousand Monte Carlo simulations in step 5.

4.2.1 Step 1: Build an initial model of the engineering system to measure value and performance.

In this case study, the metric for assessing value and performance is NPV. The main uncertain variables are the market value and the development cost of built apartment property per square foot. When an apartment building is completed, developers get its total value as revenue. This is determined by total apartment unit surface area multiplied by market value of built property per square foot. The same applies to development costs.

The initial model consists of a DCF Excel® spreadsheet using standard projections of market value of built property and development costs. For simplicity, the model assumes that only one phase can begin each year. Therefore, developers wait a year before beginning a new phase, even if the previous one is half completed. The model is developed from the following assumptions, which are partially inspired from the case described by Ariizumi (2006):

- The deterministic forecast is that market value of built property is currently evaluated at \$350/SF and increases linearly at a rate of 2.5% per year;
- Development costs are currently evaluated at \$220/SF and increase linearly with inflation at a rate of 2.5% per year;
- The project can be developed over twenty years, starting in 2007 until the end of 2027;
- Land acquisition cost is \$15M to be paid as soon as phase I begins;

- The park has a surface area of about 200,000 SF (about 4.6 acres) and costs \$1M to develop along with the five development phases. The cost is distributed among each phase as \$200,000 per phase;
- Infrastructure development, which includes site grading, paving, utilities, and landscaping are estimated at \$29/SF of apartment unit;
- The discount rate for market value of built apartment property (r_V) is 9%. The discount rate for construction costs (r_C) is 6%, close to currently prevailing risk-free rates.
- Development of all phases in a row benefit from cost reductions of 2.5% due to economies of scale.

To measure the static NPV, two different discount rates are used as proposed by Geltner and Miller (2006). It is difficult for developers to evaluate the "unified" opportunity cost of capital (OCC), denoted as r_U, that takes into account both market value risks and construction cost risks. The OCC for discounting future revenues used by the developer, denoted as r_V, is different from the OCC used to discount potential construction costs (r_C). Developers give construction costs a relatively large weight in the project's expected value calculation because they may turn out greater than originally projected. Therefore, a smaller discount rate r_C, around the prevailing risk-free rate, is used to discount future construction costs in the pro forma cash flow projections. The discount rate for revenues, r_V, is typically higher, and here is 9%.

In other words, since it is difficult for developers to know r_U, Geltner and Miller (2006) suggest using two different discount rates for real estate development projects such that

$$\frac{V_T - K_T}{(1+E[r_U])} = \frac{V_T}{(1+E[r_V])^T} - \frac{K_T}{(1+E[r_C])^T}$$

where V_T and K_T are the market value and construction cost of built property at time T.

Table 4.7 summarizes the initial estimated value (V_0) and construction costs (K_0) breakdown per square foot for the development project. Figure 4.13 shows the initial DCF model used to compute the project's NPV under deterministic market value of built property and development cost projections (Figure 4.14).

Table 4.7: Summary of market value (V_0) and construction cost (K_0) figures for the apartment development project (in $millions).

Phase	SF	V_0	V_0/SF	Infrastructure Costs	Dev. Costs	K_0	K_0/SF
I	50,000	$17.5	$350	$1.5	$11.0	$12.5	$249
II	80,000	$28.0	$350	$2.3	$17.6	$19.9	$249
III	90,000	$31.5	$350	$2.6	$19.8	$22.4	$249
IV	110,000	$38.5	$350	$3.2	$24.2	$27.4	$249
V	100,000	$35.0	$350	$2.9	$22.0	$24.9	$249
Total	**430,000**	**$150.5**		**$12.6**	**$94.6**	**$107.2**	

Year	2007	2008	2009	2010	2011	2012	2013
Period	0	1	2	3	4	5	6
Built property value per SF ($)	$350	$359	$368	$377	$386	$396	$406
Dev't cost per SF ($)	$220	$226	$231	$237	$243	$249	$255
Phase I value	$0	$0	$18,385,938	$0	$0	$0	$0
Phase I dev't cost	$10,725,000	$0	$0	$0	$0	$0	$0
Phase II value	$0	$0	$0	$30,152,938	$0	$0	$0
Phase II dev't cost	$0	$17,589,000	$0	$0	$0	$0	$0
Phase III value	$0	$0	$0	$0	$34,770,106	$0	$0
Phase III dev't cost	$0	$0	$20,282,316	$0	$0	$0	$0
Phase IV value	$0	$0	$0	$0	$0	$43,559,216	$0
Phase IV dev't cost	$0	$0	$0	$25,409,234	$0	$0	$0
Phase V value	$0	$0	$0	$0	$0	$0	$40,589,270
Phase V dev't cost	$0	$0	$0	$0	$23,676,787	$0	$0
Acquisition cost	$15,000,000	$0	$0	$0	$0	$0	$0
Infrastructure cost	$1,426,911	$2,340,134	$2,698,467	$3,380,580	$3,150,086	$0	$0
Park development cost	$195,000	$199,875	$204,872	$209,994	$215,244	$0	$0
Value of built property	$0	$0	$18,385,938	$30,152,938	$34,770,106	$43,559,216	$40,589,270
Total cost	$27,346,911	$20,129,009	$23,185,655	$28,999,808	$27,042,116	$0	$0
Net value	-$27,346,911	-$20,129,009	-$4,799,717	$1,153,130	$7,727,990	$43,559,216	$40,589,270
PV of built property	$115,903,253						
PV total cost	$112,740,379						
NPV	**$3,162,873**						

Figure 4.13: Pro forma statement and DCF model based on deterministic projections for future revenues and costs of the apartment development project.

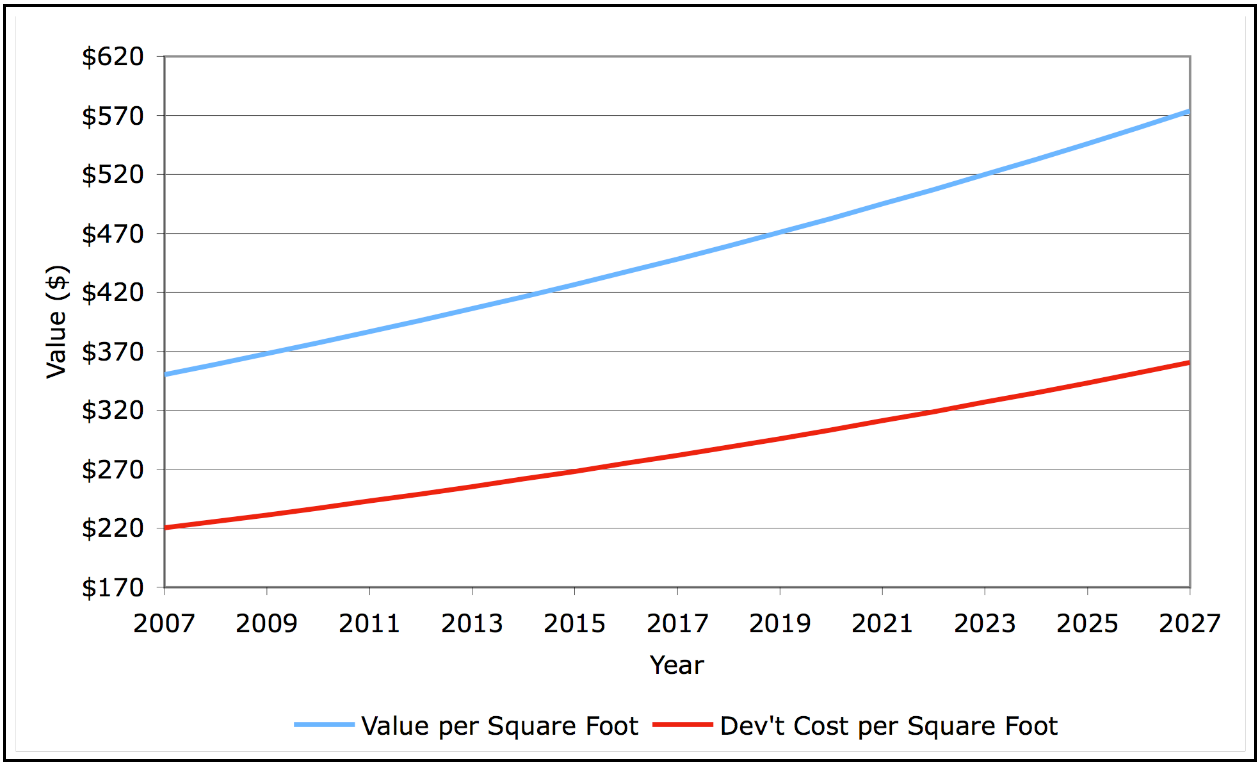


Figure 4.14: Deterministic projections of market value of built apartment property and development cost per square foot.

This initial analysis, based on the above assumptions, shows that the maximum NPV is obtained by building all phases in a row. This provides a NPV of $3.2M. This static case analysis corresponds to engineering and management practice where uncertainty is not recognized in the model and flexibility is not used to adapt towards it.

4.2.2 Step 2: For each source of uncertainty, propose a limited set of uncertain variable scenarios and review initial model.

For simplicity, market value of built property is the only source of uncertainty considered in this case study. Development cost is assumed to increase at the same constant rate as inflation, assumed to be 2.5% annually.

A set of three market value scenarios is created to support the creation of a catalog of operating plans. The method that should be used to find relevant scenarios is explained in Section 3.2. In order to simplify the demonstration, the method is not applied fully here. The market value scenarios are chosen to represent simple situations program managers might have to deal with in reality.

Scenario 1 is chosen to represent an excellent evolution of market value through the lifecycle of the project with a high initial value and 3.5% annual growth. Scenario 2 is chosen to represent a situation where market allows construction at first, and then is unfavorable to development around 2013. Scenario 3 represents the case where no development should occur at all. The three market value scenarios are categorized by their initial values, as shown in Table 4.8. These categories are used to classify simulated market value scenarios in step 5 of the analysis.

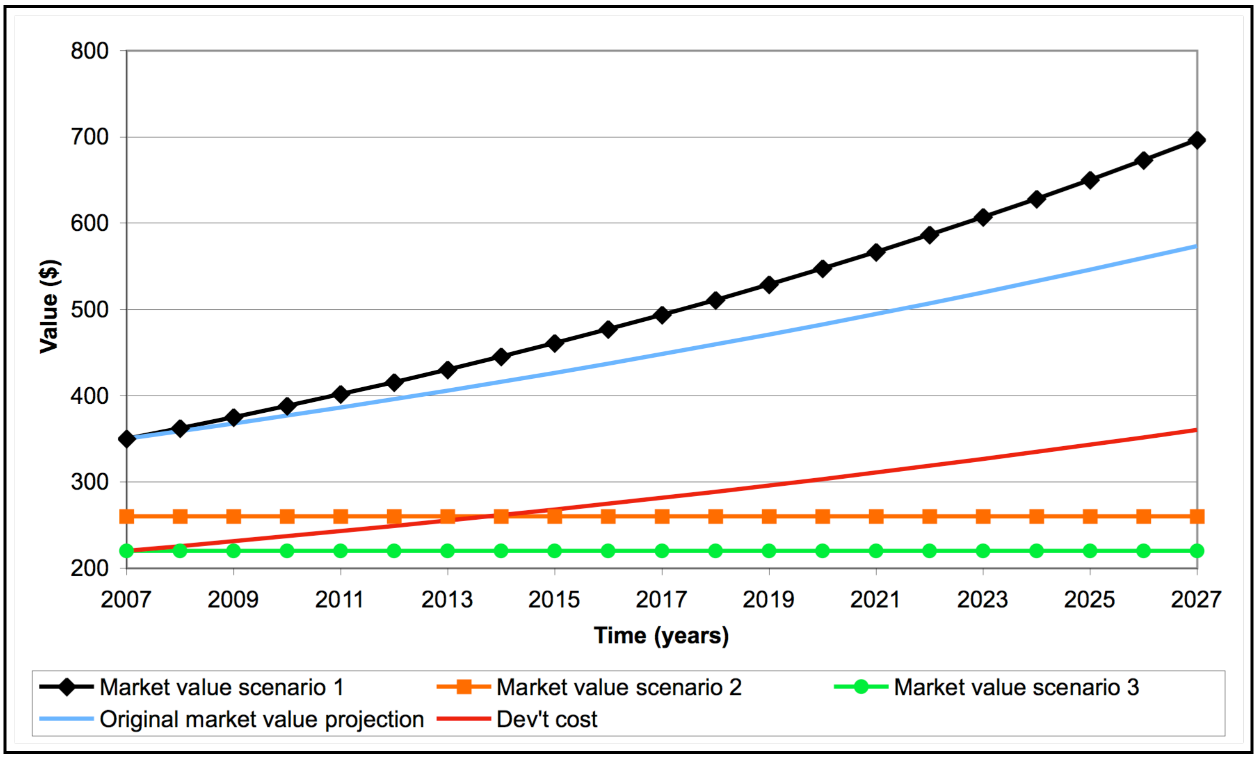


Figure 4.15: Selected market value scenarios for application of the adaptive OFAT search algorithm and creation of the catalog of operating plans. Initial projections of market value of built property and development cost are also shown for reference.

Table 4.8: Initial value for the three market value scenarios. This value is used to categorize the different scenarios and classify simulated market value scenarios in step 5 of the analysis methodology.

Market Value Scenario Category	Initial Value
1	$350
2	$260
3	$220

4.2.3 Step 3: Determine the main sources of flexibility in the system and incorporate in the model.

The following sources of flexibility are incorporated in the model to benefit from upside opportunities in uncertain market value of built property. This situation is best represented by scenario 1 in step 2. Flexibility is also acquired to guard against potential losses when market value is unfavorable, which is best represented by scenario 3.

4.2.3.1 Flexibility "In" Design

The first source of flexibility to acquire "in" design is to develop a park with the initial phase to attract more buyers and increase market value of the development site. Since the park is built all at once instead of in sync with the five phases, it is similar to a call option. The strike price of $1M is paid to exercise the option (developing the park), and a percentage increase in value above simulated market value is provided as the benefit of exercising the option. Here, 10% increase above simulated market value is suggested. This increase in market value however occurs only when the market value of built property is on the rise, or growing from the previous year. This reflects the fact that buyers are not necessarily willing to pay more for this extra feature if the market is depressed and prices are low anyway. Hence, when market value is depressed, this extra feature provides no additional benefit. On the other hand, this flexibility contributes in increasing NPV in subsequent years when markets go well.

4.2.3.2 Flexibility "In" Operations

The second source of flexibility exploits the flexibility to expand the different phases of the project at strategic times. It consists of the ability for program managers to wait until market conditions are favorable for a subsequent phase. The criteria for deciding on expansion to a subsequent phase is based on market value of built property being greater than a certain threshold percentage above development costs at a given time. Decision to develop at time T results in construction costs being incurred at T, and the phase being completed at $T + 2$ years. Since development is broken down according to the timing of the different phases, there is no economy of scale and therefore no construction cost reduction associated with this flexible case.

4.2.3.3 Flexibility "On" Project

The third source of flexibility is to abandon the project and sell undeveloped land at the end of the 20-year project lifecycle, or if profit generated by selling the land is higher than profit made by developing it. This case assumes a starting price of undeveloped land of $3M that evolves at the same rate as market value of built property, and no rezoning cost.

4.2.3.4 Modifying the Model to Incorporate Flexibility

The first source of flexibility consists of building a park upfront to attract potential buyers and improve market value. Designers investigate the effect of building the park along with different apartment phases or with the initial phase only. The benefit upon additional market value is reduced the more phases it takes to build the park because new buyers are not attracted by the beauty of the completed site, and are not necessarily willing to pay more because of it. Building the park in phases however reduces upfront capital expenditures in the first year and distributes them over subsequent phases.

The first management decision rules consists of building the park upfront in phase I for $1M along with a 10% increase in market value over simulated market value when market value is on the rise from the previous year. The second possibility is to build the park in phases I and II for \$500,000 in both phases, together with a 5% increase in market value when market value is on the rise from the previous year. The third possibility is to build the park across all phases I to V with no increase in market value.

The second source of flexibility exploits the ability to expand in phases at strategic times. Program managers decide to wait for the next phase development until market value of built property attains a certain percentage over development costs. The following three percentage criteria over development cost are suggested for deciding to expand: 10%, 50%, and 100%. For example, if at a given time development cost for a phase is \$10M and a 10% percentage criterion is selected, market value of built property needs to be at least \$11M for development to occur. Merely being above \$10M is not sufficient.

The source of flexibility to abandon development and sell remaining land is exploited through three different decision rules. Rule 1 is based on a decision to abandon if development profit is lower than abandonment profit, development value is above the percentage criteria for expansion, and at least one phase is built (because payment is made to acquire the land only when phase I is launched). If program managers do not acquire the land, they cannot abandon it and get sales value from it, which is the reason for the last criterion. Rule 2 is based on having development profit higher than abandonment profit without the need to fulfill the percentage criteria for expansion. It is expected that abandonment will occur more frequently with this latter decision rule. Rule 3 does not allow abandonment throughout years 0 to 19. It is only allowed in the final year and for land remaining from undeveloped phase(s). Figure 4.16 summarizes these design and management decision rules.

		Levels		
DEs and Management DRs	Description	-	o	+
A	Abandonment option	Rule 1	Rule 2	Rule 3
B	Value over cost criterion for expanding	10%	50%	100%
C	Number of phases for developing the park	1	2	5

Figure 4.16: Design elements and management decision rules for the creation of the catalog of operating plans in the real estate development project. "DE" means design element, and "DR" means decision rule. The possible values for each design element or management decision rule is known as a level.

4.2.4 Step 4: Search the combinatorial space and create the catalog of operating plans.

Adaptive OFAT was used to explore the combination of design elements and management decision rules producing the highest NPV for all three market value scenarios introduced in Figure 4.15. Like in the parking garage case study, demonstration of the search process is shown only for the first market value scenario, which gives rise to the first operating plan in the catalog. This demand scenario is shown in Figure 4.17. The remainder of the analysis is shown in the Appendix section.

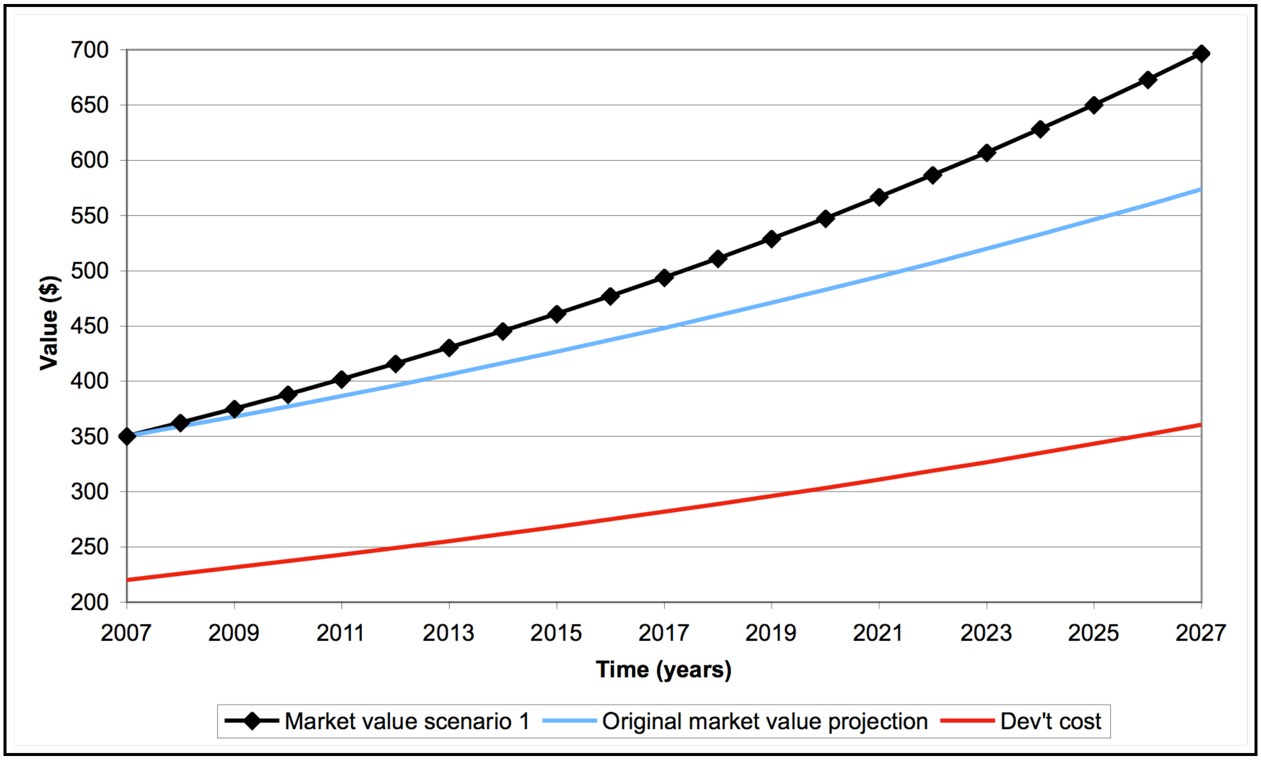


Figure 4.17: Market value scenario 1 is used in this demonstration of the adaptive OFAT process for the real estate development project.

The baseline experiment and the OFAT sequence are determined randomly for each market value scenario, and those for scenario 1 are shown in Table 4.9. Results from this analysis are also shown in the Appendix section for different baseline experiments and OFAT sequences, also generated randomly.

Table 4.9: Baseline experiment and OFAT sequence used to explore the combinatorial space for market value scenario 1.

DEs and Management DRs	Description	Baseline Experiment	OFAT Sequence
A	Abandonment option	Rule 2	A
B	Value over cost criterion for expanding	10%	C
C	Number of phases for developing the park	5	B

The adaptive OFAT process is applied as shown in Figure 4.18, and the first operating plan emerging from this analysis is shown in Table 4.10. In the table, the operating plan is accompanied by a development plan to form a complete operating plan. This demonstrates another way to conceive an operating plan, which in this case is a combination of design and management decision rules accompanied by a development plan.

Experiment	DE and Management DR changed	Level changed to:	Output = NPV	Best output before step	Keep change?
1 (baseline)			$ 5.5		
2	A	Rule 1	$ 5.5	$ 5.5	No
3	A	Rule 3	$ 5.5	$ 5.5	No
4	C	1	$ 17.5	$ 5.5	Yes
5	C	2	$ 11.5	$ 17.5	No
6	B	50%	$ 17.5	$ 17.5	No
7	B	100%	$ - 7.7	$ 17.5	No

Figure 4.18: Adaptive OFAT process exploring the combinatorial space for the best combinations of levels under market value scenario 1.

Table 4.10: Best operating plan selected for market value scenario 1. In this case, expansion occurs in a row starting in the first year. Management decision rules (a) are associated with a development plan (b) to form a complete operating plan.

DEs and Management DRs	Description	Best Operating Plan for Scenario 1
A	Abandonment option	Rule 2
B	Value over cost criterion for expanding	10.00%
C	Number of phases for developing the park	1

(a)

Op. Plan	Year		2007	2008	2009	2010	2011	2012	2013	2014	2015
1	Phase I	Develop? Abandon? Wait?	Develop								
	Phase II	Develop? Abandon? Wait?		Develop							
	Phase III	Develop? Abandon? Wait?			Develop						
	Phase IV	Develop? Abandon? Wait?				Develop					
	Phase V	Develop? Abandon? Wait?					Develop				

(b)

The same search algorithm is applied to the two remaining market value scenarios so that a catalog of three operating plans is created and shown in Table 4.11.

Table 4.11: Catalog of operating plans obtained from the analysis of three market value scenarios under the adaptive OFAT algorithm. Management decision rules for each operating plan (a) are associated with a development plan (b) to form a complete operating plan.

DEs and Management DRs	Description	Op. Plan 1	Op. Plan 2	Op. Plan 3
A	Abandonment option	Rule 2	Rule 2	Rule 2
B	Value over cost criterion for expanding	10%	10%	10%
C	Number of phases for developing the park	1	5	5

(a)

Op. Plan	Year		2007	2008	2009	2010	2011	2012	2013	2014	2015
1	Phase I	Develop? Abandon? Wait?	Develop								
	Phase II	Develop? Abandon? Wait?		Develop							
	Phase III	Develop? Abandon? Wait?			Develop						
	Phase IV	Develop? Abandon? Wait?				Develop					
	Phase V	Develop? Abandon? Wait?					Develop				
2											
	Phase I	Develop? Abandon? Wait?	Develop								
	Phase II	Develop? Abandon? Wait?		Develop							
	Phase III	Develop? Abandon? Wait?			Develop						
	Phase IV	Develop? Abandon? Wait?				Wait	Wait	Abandon			
	Phase V	Develop? Abandon? Wait?					Wait	Abandon			
3											
	Phase I	Develop? Abandon? Wait?	Wait	Wait	Wait	Wait	Wait	Wait	Wait	Wait	Wait
	Phase II	Develop? Abandon? Wait?		Wait	Wait	Wait	Wait	Wait	Wait	Wait	Wait
	Phase III	Develop? Abandon? Wait?			Wait	Wait	Wait	Wait	Wait	Wait	Wait
	Phase IV	Develop? Abandon? Wait?				Wait	Wait	Wait	Wait	Wait	Wait
	Phase V	Develop? Abandon? Wait?					Wait	Wait	Wait	Wait	Wait

(b)

One should note that in order to find the second operating plan, it is necessary to skip decision rule B in the adaptive OFAT process, which is the expansion decision criterion. This is because the NPV values generated during the OFAT search are all negative, as shown in the Appendix section. Therefore increasing the expansion decision criteria to 50% and 100% generates an operating plan similar to plan 3 in Table 4.11 where investment never occurs.

Since program managers have an operating plan that suggests complete expansion in a row with operating plan 1, and a plan suggesting no investment at all in operating plan 3, it is interesting to have an operating plan that handles intermediate situations. Even if the adaptive OFAT process generates negative NPV values using scenario 2 (with an initial and constant market value of \$260 per square foot), this intermediate operating plan can still generate positive NPV values in step 5 for simulated market value scenarios having an initial value between \$260 and \$350 per square foot. It might therefore be interesting to keep this operating plan in the catalog.

This situation is an example where designers' judgment can be used in the adaptive OFAT process to suit their design and management needs. In this case, this shows that designers can apply the adaptive OFAT process in a flexible manner to find intermediate solutions.

4.2.5 Step 5: Assess the Value of the Catalog of Operating Plans

The catalog of operating plans is tested under a set of two thousand Monte Carlo simulations of market value of built property. It is compared to the inflexible case where are all phases are developed in a row, with the park developed in sync with the five phases. This development strategy is the one producing the highest NPV based on assumptions about market value and development cost.

The model incorporates uncertainty around market value of built property through random variations around the overall growth rate and initial value of the scenario projected initially. The growth rate can be 50% off the 2.5% annual projection. Initial value can also vary by 50% off the $350 projection. A volatility of 15% is introduced around each annual growth value, and samples are taken from a uniform probability distribution. An example of simulated market value pattern is shown in Figure 4.19.

Each of the two thousand simulations is categorized as one of the three market value scenarios shown in Figure 4.15, and associated to the corresponding operating plan. The criterion for classifying simulated market value patterns is the initial value. Looking at Table 4.8 for instance, a market value pattern with initial value beyond $350/SF will be associated to operating plan 1. A pattern with an initial value between $260/SF and $350/SF is associated with operating plan 2, and below $260 is associated to operating plan 3. Figure 4.20 shows how many simulated market value scenarios are classified in each of the three categories.

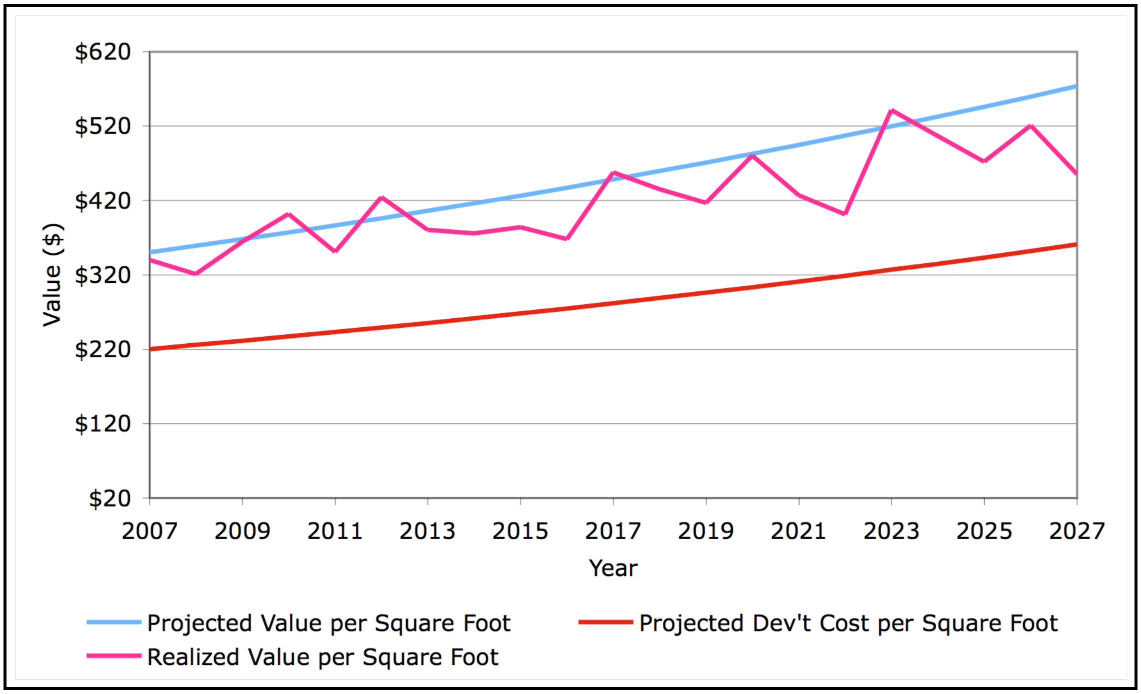


Figure 4.19: Example of one market value fluctuation from the two thousand Monte Carlo simulations used to incorporate uncertainty in the model.

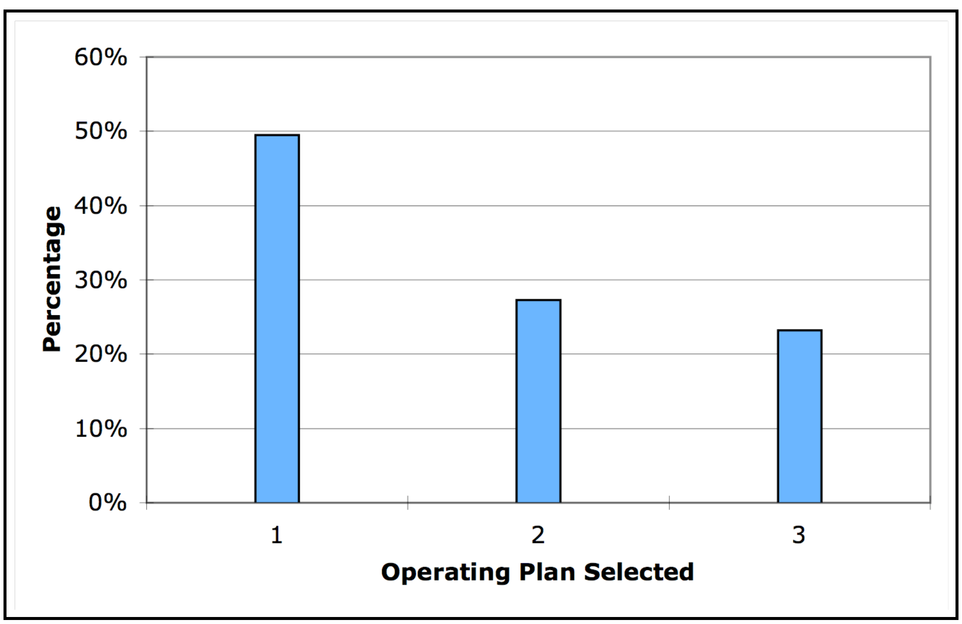


Figure 4.20: Percentage of simulated demand scenarios categorized as one of the three operating plans for the two thousand scenario simulations. Each simulated market value scenario is associated to one operating plan.

Table 4.12 summarizes the results from Monte Carlo simulations. Recognizing uncertainty and developing all phases in a row with no flexibility provides an ENPV of \$3.3M. A flexible design with a catalog of three operating plans generates an ENPV of \$16.9M. The expected improvement provided by the analysis methodology and the catalog of operating plan is worth \$16.9M – \$3.3M = \$13.6M.

Table 4.12: Summary of results comparing valuation attributes between an inflexible real estate development project with all phases developed in a row, and a flexible design with a catalog of three operating plans. In the latter case, each of the two thousand Monte Carlo simulations are categorized and assigned one of three operating plans. All values are in \$millions.

	Inflexible Design	Flexible Design with Catalog of Operating Plans	Which is Better?
Initial investment	\$ 27.3	\$ 21.4	Flex. and Catalog Better
Expected NPV	\$ 3.3	\$ 16.9	Flex. and Catalog Better
Minimum NPV	\$ -59.2	\$ -25.5	Flex. and Catalog Better
Maximum NPV	\$ 77.9	\$ 90.0	Flex. and Catalog Better
Value of Flexibility	\$ 0.0	\$ 13.6	

Table 4.12 and the VARG curve on Figure 4.21 show that using a catalog of operating plans reduces the expected initial investment by approximately \$5.9M, increases the minimum NPV by about \$33.7M, and the maximum NPV by \$12.1M. Both upsides and downsides are clearly improved by the introduction of flexibility and a catalog of operating plans.

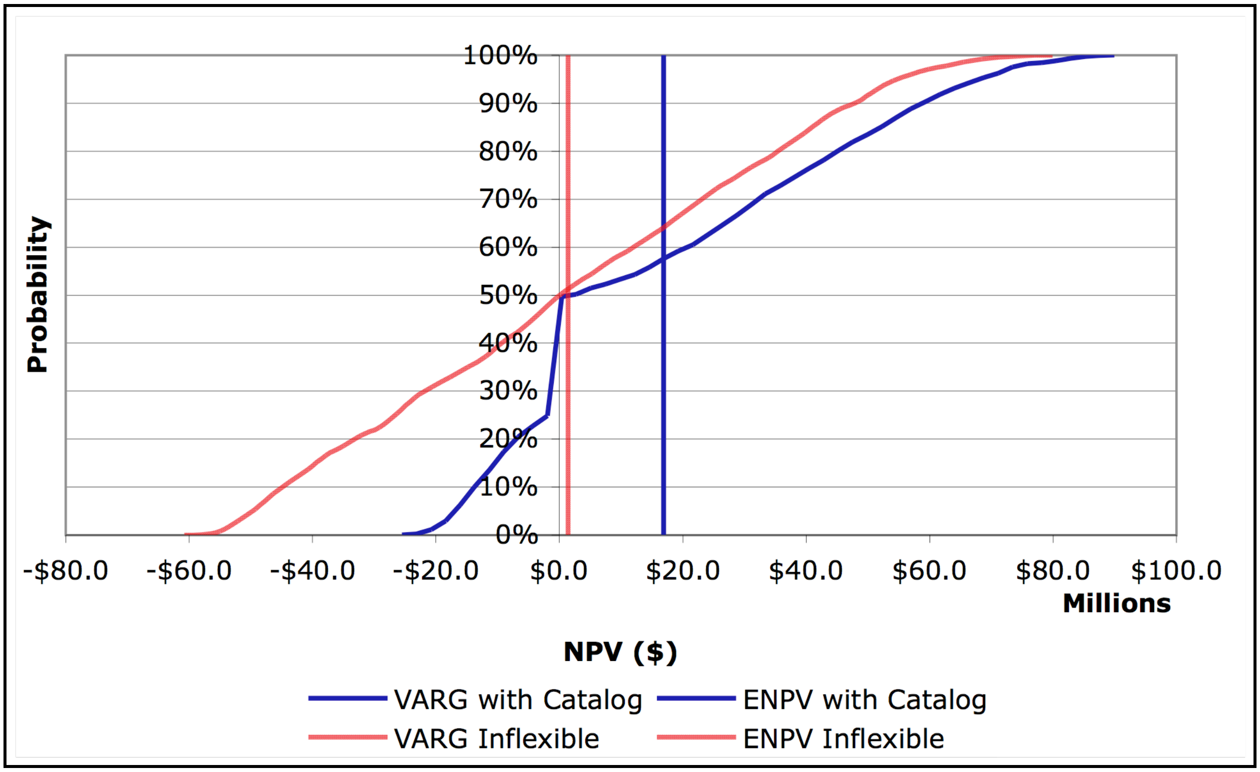


Figure 4.21: VARG curves resulting from Monte Carlo simulations for both the inflexible real estate development with all phases developed in a row, and flexible design using a catalog of three operating plans. ENPVs for both cases are also shown.

4.3 Thesis Support

As seen in the final part of Sections 4.1.5 and 4.2.5, the analysis methodology proposed in this thesis improves the design and management of engineering systems while requiring minimal computational effort. Numerical analyses from both the parking garage and real estate development cases support this thesis. This improvement is due to incorporation of flexibility in design and management of both systems in order to take advantage of uncertainty. It is also due to more realistic value assessments that consider a limited set of uncertain variable scenarios as part of the design analysis. Not only is the ENPV compared to an inflexible system improved in both cases, but so are other attributes like minimum NPV, maximum NPV, and expected initial investment.

The remainder of this section discusses issues encountered while developing and applying the analysis methodology. The first point of discussion is whether the adaptive OFAT process finds the optimal combination of design elements and management decision rules. It almost certainly does not find an “optimal” combination because it is not a process that aims at optimizing performance measure in this mathematical connotation. It is a practical way to improve design and management decision choices within limited time.

Furthermore, the process does not necessarily generate the same catalog of operating plans depending on the baseline experiment and sequence of exploration selected. This is shown using results from the Appendix section. In the parking garage case, performing another series of adaptive OFAT experiments with different baseline experiments and OFAT sequences, under the same demand scenarios used in Section 4.1.4, produces a different catalog of operating plans (Table A.7) than the one obtained in the first analysis of Section 4.1.4 (Table 4.4). The ENPV of this new catalog and other valuation attributes (minimum and maximum NPV, expected initial investment) are however relatively similar to those obtained in the first analysis (see Table 4.5 and Table A.8). For the reader’s convenience, both catalogs of operating plans are shown in Table 4.13, together with the results from the two thousand Monte Carlo simulations in Table 4.14.

Table 4.13: Catalogs of operating plans obtained from the analysis of five demand scenarios under the adaptive OFAT algorithm for the parking garage case. a) Results are shown for the analysis presented in Section 4.1.4 where the same baseline experiment is used for all application of the adaptive OFAT algorithm, and OFAT sequences are generated randomly. b) Results are shown when different baseline experiments and OFAT sequences are used, both being generated randomly. "DE" means design element, and "DR" means decision rule.

DEs and Management DRs	Description	Op. Plan 1	Op. Plan 2	Op. Plan 3	Op. Plan 4	Op. Plan 5
A	Expansion allowed in years 0-4	Yes	Yes	Yes	Yes	Yes
B	Expansion allowed in years 9-12	Yes	Yes	No	Yes	Yes
C	Expansion allowed in years 17-20	Yes	Yes	Yes	Yes	Yes
D	Expansion decision rule (years)	2	2	2	2	4
E	Number of floors expanded by	2	3	3	1	1
F	Number of initial floors	6	5	5	4	4

(a)

DEs and Management DRs	Description	Op. Plan 1	Op. Plan 2	Op. Plan 3	Op. Plan 4	Op. Plan 5
A	Expansion allowed in years 0-4	Yes	Yes	Yes	Yes	No
B	Expansion allowed in years 9-12	No	Yes	Yes	Yes	Yes
C	Expansion allowed in years 17-20	No	No	No	No	Yes
D	Expansion decision rule (years)	3	2	2	2	4
E	Number of floors expanded by	2	2	2	1	1
F	Number of initial floors	6	6	4	4	4

(b)

In the real estate case however, repeating the OFAT search algorithm using different baseline experiments and OFAT sequences produces the same catalogs of operating plans, and also similar values under the two thousand Monte Carlo simulations of market value scenarios. The catalogs are shown in Table 4.11 and Table A.13, while the results from Monte Carlo simulations are shown in Table 4.14 and Table A.14. The resulting VARG curves are also similar, as seen on Figure 4.21 and Figure A.8.

Table 4.14: Summary of results comparing valuation attributes between an inflexible parking garage design with five initial floors, and a flexible design with a catalog of five operating plans. a) Results are shown for the analysis presented in Section 4.1.4 where the same baseline experiment is used for all application of the adaptive OFAT algorithm, and OFAT sequences are varied randomly. b) Results are shown when different baseline experiments and OFAT sequences are used, both being generated randomly. In both cases, each of the two thousand Monte Carlo simulations of demand scenarios are categorized and assigned one of five operating plans.

	Inflexible Design	Flexible Design with Catalog of Operating Plans	Which is Better?
Expected initial investment	$ 18.1	$ 16.3	Flex. and Catalog Better
Expected NPV	$ 2.9	$ 4.9	Flex. and Catalog Better
Expected NPV minus expected cost of flexibility	$ 2.9	$ 4.2	Flex. and Catalog Better
Minimum NPV	$ -19.5	$ -18.8	Flex. and Catalog Better
Maximum NPV	$ 8.3	$ 20.5	Flex. and Catalog Better
Value of catalog of flexible operating plans	$ 0.0	$ 1.3	

(a)

	Inflexible Design	Flexible Design with Catalog of Operating Plans	Which is Better?
Expected initial investment	$ 18.1	$ 15.5	Flex. and Catalog Better
Expected NPV	$ 2.9	$ 5.1	Flex. and Catalog Better
Expected NPV minus expected cost of flexibility	$ 2.9	$ 4.3	Flex. and Catalog Better
Minimum NPV	$ -19.5	$ -15.6	Flex. and Catalog Better
Maximum NPV	$ 8.3	$ 17.3	Flex. and Catalog Better
Value of catalog of flexible operating plans	$ 0.0	$ 1.4	

(b)

There is an interesting feature on Figure A.8, reproduced here at the reader's convenience, worth discussing here. The discussion about the fact that adaptive OFAT does not always generate same results is continued a few paragraphs below.

On Figure 4.22, one sees around a cumulative probability of 50% that the NPV values obtained with the catalog of operating plans are lower than with an inflexible design. This is due to the flexibility to abandon the project right at the beginning if market conditions are unfavorable for development of the real estate project, and to weak positive NPVs produced when market conditions are barely favorable for development. If the flexibility to abandon the project is exercised, it creates a scenario with zero NPV because developers never acquire the land, and do not develop any building. The frequency of occurrence of this abandonment scenario is shown in Figure 4.23.

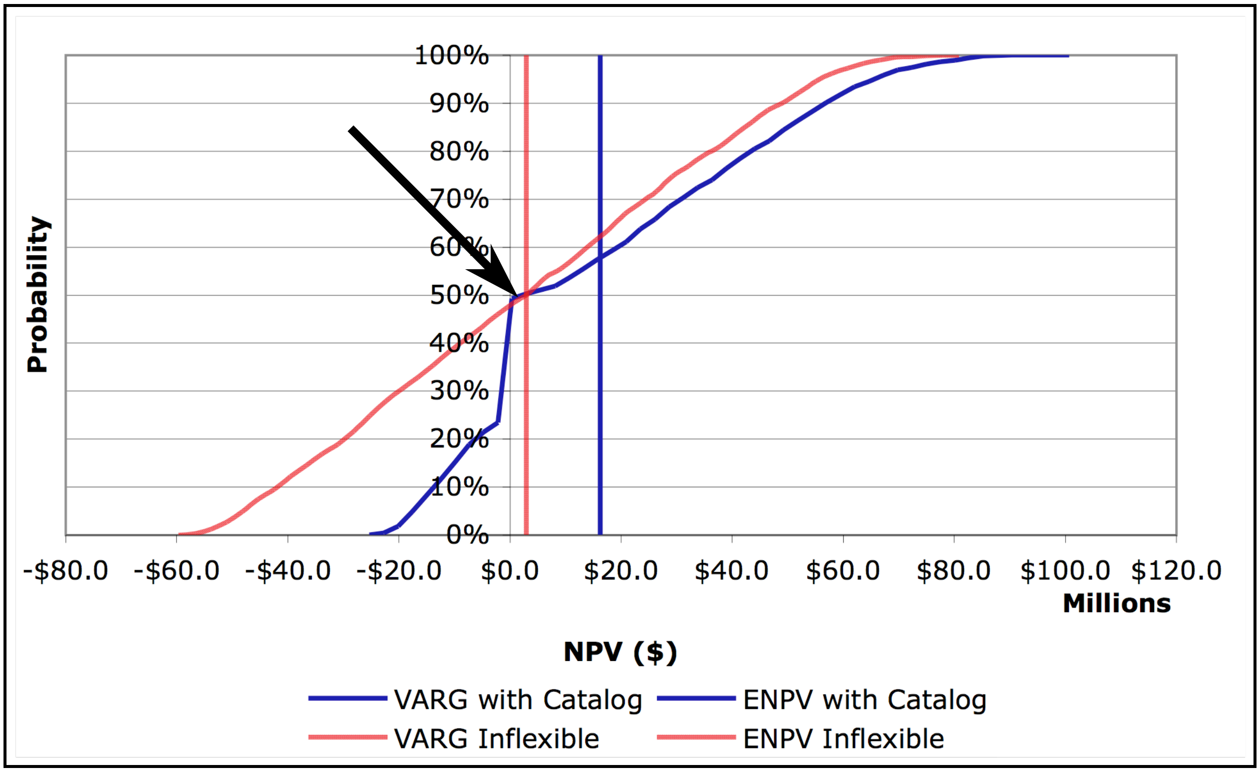


Figure 4.22: VARG curves and ENPVs resulting from Monte Carlo simulations for both the inflexible real estate development with all phases developed in a row, and flexible design using a catalog of three operating plans. This is the case where new experiments are done, as compared to the first set of experiments presented in Section 4.2.4, as shown on Figure A.8. The arrow points out an interesting feature of the VARG curves, where NPVs for the case with the catalog of operating plans are lower than those produced by the inflexible case (around 50% cumulative probability). This is due to the flexibility of abandoning the project if market conditions are unfavorable right at the outset, and to the cost of acquiring the flexibility when market conditions are barely favorable for development.

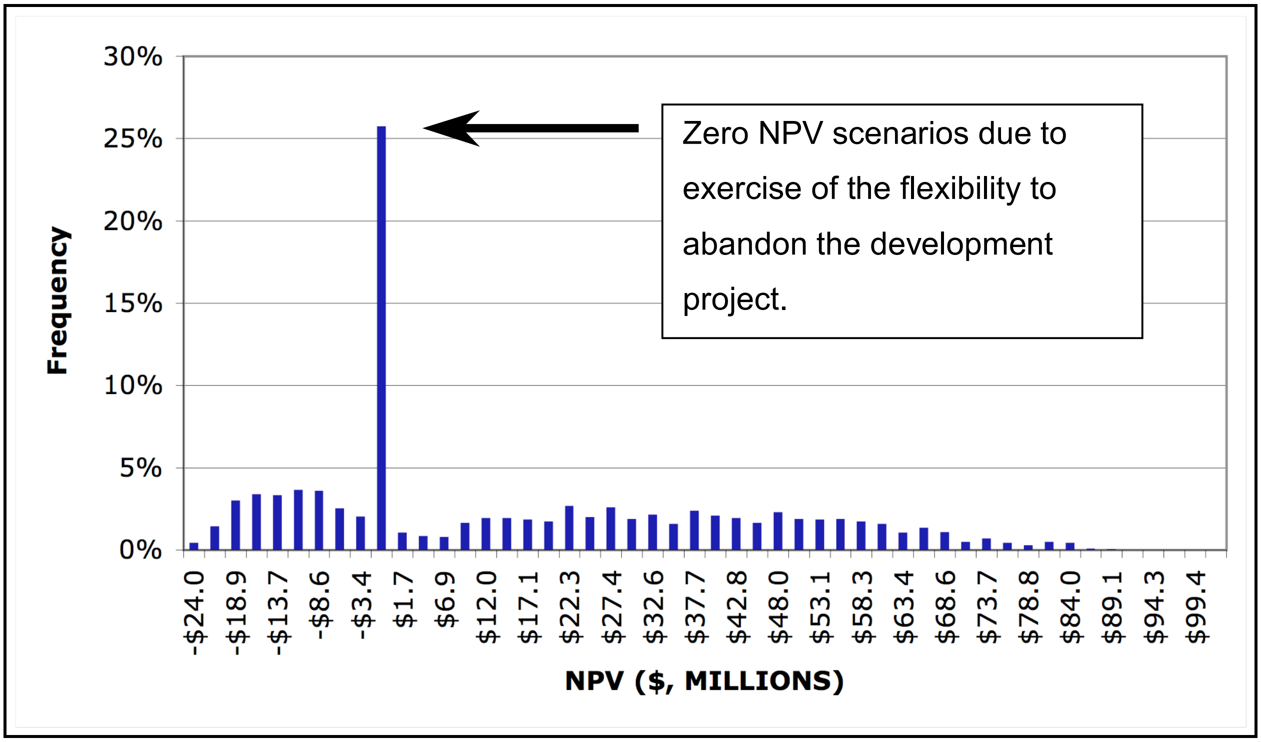


Figure 4.23: NPV distribution for the real estate development case study when different baseline experiments and OFAT sequences than those presented in Section 4.2.4are used, as shown in the Appendix section. The spike around NPV = $0 shows the number of scenarios where the flexibility to abandon the project is exercised.

This type of abandonment scenario explains the sudden jump near NPV = $0 for the case with a catalog of operating plans. Then, just to the right of these zero-NPV scenarios on Figure 4.22 are a few scenarios with small positive NPVs that are created when market conditions are barely favorable to development. In the flexible case with operating plans, development is slightly more expensive to developers because they have to pay a premium to acquire the flexibility compared to the inflexible case. Because market conditions are barely favorable to development, developers can hardly recoup their investment, which creates positive but small NPVs. This is why in those few cases a flexible design using a catalog of operating plans produces NPVs slightly lower than in the inflexible case. Therefore, combining the sudden jump near zero-NPV scenarios, and the fact that weak positive NPVs are produced when market conditions are barely favorable to development, explain why the catalog of operating plans produce lower NPV values around the 50% cumulative probability mark on Figure 4.22.

Coming back to the discussion about the fact that adaptive OFAT does not always generate the same answer, this thesis argues that this fact is relevant but not central to the purpose of the analysis methodology presented here. The goal here is to develop an approach that improves design and management of complex systems compared to the case where an inflexible design and management plan is considered. By investigating the combinatorial space further, chances are increased of finding a better solution even if the optimal solution is not found. Also, since the goal is also to improve analysis while minimizing additional computational effort, the current methodology represents a good tradeoff between time devoted to the analysis and the quality of achieved solution.

The second point of discussion is related to the flexible application of the adaptive OFAT algorithm made in this thesis. First, the process is not applied in the context of statistical experiment design where many experiments are run to find the best combination of design elements and management decision rules. The process is applied here to find the best combination of design and management decision rules under only *one* particular uncertain variable scenario instead of many, as typically done in statistical experiment design. Also, designers who are aware of more efficient design and management combinations are free to incorporate this knowledge and skip some combinations while applying the adaptive OFAT process. This is done for scenario 2 of the real estate case study, as explained at the end of step 4 of the analysis methodology in Section 4.2.4.

This aspect is important in the analysis methodology. The purpose of introducing the search algorithm is to have a structured approach to explore the combinatorial space *specifically* when it is not obvious for designers to do so. The search process can however be replaced by any approach designers feel relevant in order to find useful operating plans under a given set of uncertain variable scenarios.

The third point is related to the percentage of each operating plan that is selected in the simulations, as shown in Figure 4.10 and Figure 4.20. As observed on Figure 4.10 for the parking garage case, operating plans 1 and 5 should not occur as frequently as other intermediate operating plans because they represent infrequent boundary situations. Operating plan 1 corresponds to the ideal and infrequent situation of very fast demand growth in early years, while operating plan 5 corresponds to the equivalently infrequent situation of slow and nearly constant growth during that time. It makes sense for this case study to see operating plans 2, 3, and 4 take the majority of counts. For the real estate development project (Figure 4.20), it is reasonable that operating plans 2 and 3 are not used as often as operating plan 1. This is because these two operating plans should be used when market conditions are unfavorable, which does not occur very frequently.

The fourth point of discussion relates to the value assessment of the catalog of operating plans in the case of the parking garage. In step 5 of the analysis methodology and as shown in Table 4.14a, the ENPV of the catalog of operating plans is \$4.2M compared to \$2.9M for the inflexible case with one operating plan. In (de Neufville et al., 2006), under two thousand similar Monte Carlo simulations, the authors find an ENPV of \$5.1M using a flexible design with four initial floors, and a decision rule to expand by one floor when demand is higher than capacity for two consecutive years.

One explanation for the lower ENPV obtained with the catalog approach is that the operating plans are not assigned properly to simulated demand scenarios in the value assessment part of the analysis methodology (step 5). Using a criterion that only looks at growth between years one and five may not be sufficient to characterize demand scenarios adequately. Future work will apply the suggested method of Section 3.2 for finding uncertain variable scenarios that are more representative of reality, and implement a better classification algorithm in Excel® to classify simulated scenarios more appropriately. Considering initial value of demand as well as growth rate between first and final years might bring improvement to this categorization phase.

The final point of discussion is whether the number of steps proposed in the analysis methodology is appropriate for its intended purpose. Even though the current proposal is for five distinct steps, a lot is accomplished in each step so that the structure could be broken down further into more steps if necessary. Also, the order can be manipulated to be more flexible depending on designers need. For instance, instead of assessing the value of the inflexible design that recognizes uncertainty in step 5, this could be done in step 2 as part of selecting a limited set of uncertain variable scenarios. Moreover, determining how much value is added by the analysis methodology compared to an inflexible design is not necessary. In this thesis, this is done for pedagogical reasons. This sub-step can be skipped altogether if designers acknowledge that the methodology proposed here brings more realism to their analysis by considering explicitly uncertain variable scenarios as part of the creation of the catalog of operating plans.

Chapter 5 – Barriers to Implementation and Policy Considerations

We live in a world where human, financial, and material resources are becoming increasingly scarce to emerging and developed nations. In the next few decades, the rising of China and India as economical superpowers, accompanied by a rising of the Earth's population and living standards, will continue to exacerbate pressures on the environment and between social groups for more efficient use and distribution of resources. Flexibility can play a very important role in sustaining this economic growth worldwide since it favors efficient use of human, financial, and material resources.

Flexibility can be very important as well for industry and government leaders since it increases value and performance of innovative technologies and complex systems. The analysis methodology introduced in this thesis, together with tools to find useful sources of flexibility (Sections 2.4), contributes in easier dissemination of ideas related to the implementation of flexibility. It proposes a simple and structured approach to consider and incorporate flexibility in a way that extracts additional value from uncertainty.

Concepts presented in this thesis however face a considerable burden, which is to reach their intended audience in the engineering and management communities. Even if flexibility is shown in several academic works to improve value and performance (de Neufville et al., 2006; de Weck et al., 2004; Faulkner, 1996; Kalligeros, 2006; Nichols, 1994;), the benefits will diffuse in practice only if decision-makers can understand them, and if flexibility can be shown to bring additional value and performance to their program. Another burden can be due to methodological "lock-in" that occurs when analytical methods for investment and management decisions have been used for several years, if not decades. When a firm has been using a method for analyzing investment projects for years, it is not willing to give it up easily even if another is shown to provide more realistic results.

This means the concepts presented here involve a paradigm change compared to current engineering and management practice. This change however needs to be done with pragmatism.

This is because industry and government agencies are not necessarily ready or interested in 1) implementing new ideas that involve changing already existing rules and mandates 2) implementing analysis methodologies that require more work than current methods 3) having to do so if the incentives are not clearly defined and demonstrated.

The policy component of this thesis analyzes in turn these three main barriers to implementation of the analysis methodology in real practice. In showing how the methodology can help alleviating them, the chapter also considers the reality of industry and government stakeholders involved in the design and management of engineering systems.

5.1 Existing Rules and Mandates

One barrier to implementation of a new methodology in industry and government is due to methodologies that are already in use. A methodology for assessing cost of new investment projects needs to be shown to fail before a new one can be considered. This phenomenon is analogous to Max Planck's famous quote that "science progresses funeral by funeral".

This phenomenon is normal since most firms and government agencies try to accomplish their mission the best they can, with the technical tools that are available at any given time. This reality however creates great inertia and barriers to the implementation of more efficient methodologies that involve new technology. The process for adoption may be quite arduous and long, especially if several new concepts need to be understood by the many stakeholders involved.

To illustrate this point, federal agencies in the United States are statutorily required to follow legislated Benefit-Cost Analysis (BCA) mandates as determined by the U.S. Office of Management and Budget (OMB) (Rivey, 2007). The BCA approach makes use of standard DCF techniques. Even though some agencies, like the Federal Aviation Agency (FAA), show openness in adopting new decision-making methodologies, the process can be very long before any substantial difference is noticed. In 1999, the FAA publicly stated that airport sponsors –

those who manage and operate the airport – are encouraged "to make use of innovative methods for quantifying benefits and costs where these methods can be shown to yield superior measures of project merit" (U.S. Federal Aviation Administration, 1999). (Rivey, 2007) however noticed little progress in implementation of real option-based approaches in government agencies, despite OMB's recognition that these can be used for policy mandate valuation (U.S. Office of Management and Budget, 2003). He suggested four years after OMB's statement a methodology that facilitates using these analytical tools as part of OMB's BCA mandates. This demonstrates that new methodologies, like those involving real options analysis, can take a long time before coming to use.

5.1.1 Proposed Solution: Remain in the Framework Already in Place

One possible approach to alleviate this barrier is to promote changes in the methodologies in use while continuing to work within the framework, rules, and constraints already present in the firm or government agency. This also implies using value assessment methods and analytical tools that are already in use, and presenting concepts that are intuitive to the target audience. The analysis methodology is designed to follow this approach.

5.1.1.1 Use Familiar Analytical Tools

Rivey (2007) suggested using a simple approach based on spreadsheets and Monte Carlo simulations to implement new methodologies of BCA to lower the barrier to implementation in U.S. government agencies. He also proposed specific applications of his methodology to airport development under FAA's authority.

In this thesis, the analysis methodology also promotes using analytical tools familiar to the firm or agency to avoid large learning curves. It suggests similar spreadsheet tools to ease the transition to value assessment tools that incorporate notions of flexibility and catalog of operating plans. The targeted audience is however free to choose the tools most suited for its purpose.

5.1.1.2 Present Useful Concepts in a Clear and Efficient Manner

Another aspect is that the methodology needs to be easily grasped by the targeted audience. Concepts in use should be presented in a way that is both natural and intuitive. In this context, the analysis methodology can be presented as a "short cut" that explicitly lists out and values a limited set of the most meaningful design and management solutions for operating the engineering system. The concept of catalog is useful when it is impossible to assess upfront all possibilities of managing the system due to computer intractability. It recognizes that industry and government has been doing very well given available analytical methods such as cost-benefit analysis and DCF. Now that computational power has significantly increased in recent years, it is time to take program analysis to the next level to benefit from such technological development.

5.1.1.3 Tailor Presentation to Targeted Audience

In order to send a clear message, the presentation needs to be tailored to the audience, and appropriate language needs to be used. If the targeted audience consists of program managers that focus on enhancing financial value, the methodology should be introduced first for what it can do before getting into technical details. As a way to capture the audience's attention, it should be introduced as a method that increases financial value of a system. Concepts of catalog can be presented afterwards, together with value assessment methods, preferably through a case application relevant to the targeted industry.

If the audience consists of engineers and designers interested in increasing performance, the methodology can also be introduced as achieving this ultimate goal. More technical details can however be presented to this kind of audience as compared to program managers.

Presentation of those concepts must also account for the kind of knowledge and language commonly used by the audience. It is possible in some cases that words like "flexibility" and "real options analysis" get mixed receptions because practitioners consider them too complex.

Therefore, words such as “alternative designs” can be used to refer to a flexible system design that compares to another inflexible one. The words “real option” and “flexibility” need not be used to present the analysis methodology, even though the methodology exploits those concepts to improve value and performance of the system.

5.2 New Concepts Introduce Additional Burden

Designers recognize the need to explore upfront the combinatorial space for design and management decision rules that increase value and performance. They may however not have time, financial, and computational resources to do so in an exhaustive manner. Furthermore, they need to present the results of their analyses to program managers in a clear and efficient manner.

Hence, another barrier to implementation of the analysis methodology is that it increases the amount of analysis to be performed before any investment decision is made. Instead of considering only one or a few design and management decision rules, the analysis methodology promotes exploring the combinatorial space more, while at the same time not devoting huge amounts of resources to do so. It also requires the understanding of a few new concepts, such as catalogs of operating plans, which necessitate some time for assimilation.

The resistance to recognizing uncertainty is also another potential barrier to implementation because it necessitates the extra analytical burden of introducing Monte Carlo simulations in the model. Because flexibility only makes sense when one recognizes uncertainty, it might be difficult for program managers to recognize the usefulness of flexibility, and therefore the potential increase in value and performance, if uncertainty is not recognized in the first place.

Even when program managers recognize uncertainty and the benefits of flexibility, it might be difficult to justify to management upfront payments to acquire it. The reason for this barrier to implementation is because flexibility may or may not be used in the future since it provides the “right, but not the obligation” to take a specific action at a later time.

5.2.1 Proposed Solutions: Promote Efficiency and Transparency

5.2.1.1 Efficiency

While the analysis methodology increases the analytical burden for all reasons mentioned above, it also provides short cuts to avoid searching the combinatorial space in an exhaustive manner. It provides tools like adaptive OFAT to guide the search and therefore explore this space more efficiently. It also benefits from increased computational power that is nowadays readily available, and uses analytical tools that are familiar to the firm. All these elements should contribute in alleviating the additional analytical burden, while providing program managers with a good opportunity to increase value and performance. The methodology allows them to do so while devoting minimal time, financial, and computational resources in searching efficiently for best design and management decision rules.

5.2.1.2 Transparency of the Overall Approach

The key to facilitate dissemination of the analysis methodology in the engineering and management communities is once again to promote transparency. Not only does the introduction of the methodology need to be clear and transparent (as detailed in Section 5.1.1), the methodology itself has to be transparent when applied by practitioners. Transparency allows program managers to show easily the evolution of design and management decisions and how these affect valuation.

As an example where a lack of transparency hinders dissemination of useful concepts, consider the sector of real estate development. Geltner and Miller (2006) explain that when pricing land for real estate sites development, the market often overlooks additional value derived from the flexibility to make strategic expansion decisions in a timely manner. Therefore, this often leads the market to undervalue lands and properties.

To solve this problem, the authors suggest using real options analysis implemented with a binomial tree approach to recognize the additional value to wait, expand, and abandon the project at strategic times. (Geltner, 2007) however recognizes that the complexity of the method and of concepts introduced in this approach hinders dissemination in industry practice. Approaches to assessing value of land still appear to not consider these sources of flexibility in real estate project development.

5.2.1.3 Transparency in Recognizing Practitioners' Expertise

The analysis methodology is most useful when it is not clear how designers and program managers should combine different design and management decision rules to improve value over current practice. This is the case where using the search algorithm adaptive OFAT is most appropriate.

While this algorithm structures the search in the combinatorial space, it does not mean that practitioners' expertise should be left aside when improving design and management decisions. If designers and program managers already have an idea of some powerful combinations to start the adaptive OFAT search, or in reverse are aware of combinations that do not make sense throughout the search, these should be incorporated in the process. If they have another good approach for searching the space, they are also encouraged to do so.

The idea promoted in this thesis is that the combinatorial space should be investigated further prior to investment decisions even if its size is large. This increases chances of not leaving out solutions that may improve value over current practice. It is perfectly appropriate for a firm or government agency to use a different exploration method. As long as more exploration occurs, there are more chances of improving value.

In that regard, one way to abstract adaptive OFAT and present it in a way that does not look like a "black-box" algorithm to practitioners is to consider that it is in fact a heuristic that says: "Try a slightly different combination, measure the system's response in your model, if it is good keep the change, if not, try another combination”. Therefore, there is no reason why managers should feel obligated to rigorously stick to adaptive OFAT in searching the combinatorial space. Rather, what is promoted behind adaptive OFAT is a Bayesian exploration method, abstracted in the words above, that structures the search for better design and management decision rules.

5.3 Incentives for Considering this New Approach

If a new methodology is considered in design and management practice, it has to clearly demonstrate that the benefits outweigh the potential costs. One way to do this is to apply the analysis methodology to realistic case studies and show how much value can be gained by considering uncertainty, flexibility, and further exploration of the combinatorial space compared to using one inflexible operating plan.

Chapter 4 of this thesis intends to do just this. It clearly demonstrates that the methodology can improve value compared to an inflexible design in a few simple and transparent steps. One must notice that such value assessment departs from the idea of only one NPV measure per project assessment scenario. It provides multi-dimensional value attributes for comparing distributions of outcomes, represented as VARG curves, such as expected initial investment, ENPV, maximum NPV, and minimum NPV.

It is true however that quantifying costs associated to increased analytical burden as presented above can be challenging. It might however be feasible to assess the costs for training current personnel, and for implementing analytical methods that do not necessitate installation of new software components.

Chapter 6 – Conclusion

This thesis starts from the premise that current practice for designing engineering systems makes simple assumptions about the environment in which the system might evolve, and fails to explore design elements and management decision rules that could provide better value and performance. It recognizes that full analysis of all possible permutations of design elements and management decision rules is impossible to accomplish, which creates a need for the heuristic "short-cut" methodology introduced in this thesis. With the rise of computational power, designers can now afford further exploration of the combinatorial space in search for flexible solutions that improve value and performance.

The catalog of operating plans proposed here inserts more realism in design analysis because it considers explicitly the effect of uncertainty on the system. The introduction of flexibility extracts additional value from uncertainty, thus allowing designers and program managers to do a better job. It also makes more efficient of material, financial, and human resources. While industry and government have been doing fairly well with traditional project analysis tools based on benefit-cost and discounted cash flow analyses, it is now time to consider an intelligent guide to interesting range of NPV analyses based on those tools

An analysis methodology is suggested to explore further the combinatorial space of complex systems and find a catalog of operating plans that improves value and performance. This is done through a search algorithm called adaptive OFAT that is typically used in statistical experiment design. A limited set of uncertain variable scenarios affecting system's performance is considered while investigating the combinatorial space at minimal extra computational cost. The methodology suggests using relatively simple analytical tools, such as Excel® spreadsheets and Monte Carlo simulations, to assess the value of flexible design and management decision rules through methods based on real options analysis. Other tools found in the literature are suggested to screen systems for sources of flexibility.

Through application to two case studies, the thesis demonstrates in financial terms that the methodology indeed improves value over inflexible design and management practice. The first case study relates to the development of a parking garage in the United Kingdom. The second case study relates to the development of a real estate project in the United States. Both cases exploit ideas of flexibility to further enhance value compared to inflexible approaches, which involve pro forma deterministic projections of uncertain variables and discounted cash flow analysis.

The reason for promoting simple analytical tools is to suit the reality of program managers who have may have relatively little time, financial, and computational resources to devote to upfront project analysis. They also have to transmit the results of their analysis in a clear and efficient way to program managers and decision-makers.

Thus, the policy component of the thesis addresses three main barriers to implementation of the analysis methodology in real-world practice: 1) existing rules and mandates in firms and government agencies create inertia and barriers to implementation of new methods 2) the analysis methodology requires somewhat more analytical work than current practice and 3) good incentives need to be provided before the methodology, or any new approach, can be seriously considered.

The following solutions are suggested to help surmounting these potential barriers. Many of them are part of the methodology itself, which is intended by construction. First, ensure that the methodology is implemented within the firm or government agency's current framework, rules, and management constraints. This is favored using familiar analytical tools, presenting new concepts in a clear manner, and tailoring presentation and language to targeted audience. Second, favor transparent presentation when introducing the methodology and promote transparency of the methodology itself, which allow program managers to follow clearly the evolution of the design and management decision process. Third, promote efficiency when searching the combinatorial space for new design and management decision rules, which is done by providing short cuts and a structured approach to guide the search. Fourth, present concrete examples that show value improvement over current practice through case studies as done in Chapter 4.

6.1 Opportunities for Future Research

One aspect of the analysis methodology that needs further improvement is the development of a structured approach to determine the most relevant design and management decision rules in the adaptive OFAT search. As it stands now, the approach is mostly based on intuition and brainstorming sessions from designers.

An interesting approach relies on future scenarios thinking as presented by (Lagarde, 2007). The author presented examples of how such methodology can be applied to supply chain management in the year 2020. It might be helpful to structure the determination of the most interesting design elements and management decision rules before starting exploration of the combinatorial space.

It might be interesting as well to provide a structured approach for finding sources of flexibility in operations of engineering systems. As presented in Section 2.4, there is good literature available for finding sources "in" design and "on" engineering systems, but not so much in that latter operational area.

One hopes that ideas and concepts presented in this thesis are useful and will benefit the engineering and management communities in the very near future.

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Appendix

Adaptive OFAT Results for the Parking Garage Case

Creating the Catalog of Operating Plans

This section presents the remainder of the adaptive OFAT analysis performed in step 4 of the analysis methodology to create the catalog of operating plans presented in Table 4.4. All demand scenarios used for this analysis are shown in Figure 4.5.

The chosen baseline experiment and OFAT sequence for each scenario is shown in Table A.1. For each operating plan, application of the adaptive OFAT process is shown, as well as the best operating plan emerging from this process.

Table A.1: Baseline experiments and OFAT sequences used to explore the combinatorial space for demand scenarios 1 to 5, as presented in the first experiments of Section 4.1.4.

FIRST EXPERIMENTS									
Scenario 1		Scenario 2		Scenario 3		Scenario 4		Scenario 5	
Baseline Exp.	OFAT Seq.	Baseline Exp.	OFAT Seq.	Baseline Exp.	OFAT Seq.	Baseline Exp.	OFAT Seq.	Baseline Exp.	OFAT Seq.
Yes	F	Yes	E	Yes	B	Yes	C	Yes	C
Yes	C	Yes	A	Yes	E	Yes	E	Yes	B
Yes	E	Yes	F	Yes	D	Yes	A	Yes	D
2	D	2	B	2	A	2	B	2	F
1	B	1	C	1	F	1	D	1	E
5	A	5	D	5	C	5	F	5	A

Creating Operating Plan 2

Experiment	DE and Management DR changed	Level changed to:	Output = NPV	Best output before step	Keep change?
1 (baseline)			$ 12.9		
2	E	2	$ 13.2	$ 12.9	Yes
3	E	3	$ 14.8	$ 13.2	Yes
4	A	No	$ 11.8	$ 14.8	No
5	F	4	$ 11.7	$ 14.8	No
6	F	6	$ 12.6	$ 14.8	No
7	B	No	$ 14.8	$ 14.8	No
8	C	No	$ 14.8	$ 14.8	No
9	D	3	$ 13.4	$ 14.8	No
10	D	4	$ 11.8	$ 14.8	No

Figure A.1: Adaptive OFAT process exploring the combinatorial space for the best combination of design elements and management decision rules under demand scenario 2. The dollar figures are in millions.

Table A.2: Best operating plan selected for demand scenario 2.

DEs and Management DRs	Description	Best Operating Plan for Scenario 2
A	Expansion allowed in years 1-4	Yes
B	Expansion allowed in years 9-12	Yes
C	Expansion allowed in years 17-20	Yes
D	Expansion decision rule (years)	2
E	Number of floors expanded by	3
F	Number of initial floors	5

Creating Operating Plan 3

Experiment	DE and Management DR changed	Level changed to:	Output = NPV	Best output before step	Keep change?
1 (baseline)			$ 9.9		
2	B	No	$ 10.1	$ 9.9	Yes
3	E	2	$ 9.2	$ 10.1	No
4	E	3	$ 10.8	$ 10.1	Yes
5	D	3	$ 10.4	$ 10.8	No
6	D	4	$ 9.6	$ 10.8	No
7	A	No	$ 10.4	$ 10.8	No
8	F	4	$ 10.8	$ 10.8	No
9	F	6	$ 6.6	$ 10.8	No
10	C	No	$ 10.8	$ 10.8	No

Figure A.2: Adaptive OFAT process exploring the combinatorial space for the best combination of design elements and management decision rules under demand scenario 3. The dollar figures are in millions.

Table A.3: Best operating plan selected for demand scenario 3.

DEs and Management DRs	Description	Best Operating Plan for Scenario 3
A	Expansion allowed in years 1-4	Yes
B	Expansion allowed in years 9-12	No
C	Expansion allowed in years 17-20	Yes
D	Expansion decision rule (years)	2
E	Number of floors expanded by	3
F	Number of initial floors	5

Creating Operating Plan 4

Experiment	DE and Management DR changed	Level changed to:	Output = NPV	Best output before step	Keep change?
1 (baseline)			$ 6.4		
2	C	No	$ 6.4	$ 6.4	No
3	E	2	$ 3.8	$ 6.4	No
4	E	3	$ 3.7	$ 6.4	No
5	A	No	$ 6.4	$ 6.4	No
6	B	No	$ 6.4	$ 6.4	No
7	D	3	$ 6.0	$ 6.4	No
8	D	4	$ 5.4	$ 6.4	No
9	F	4	$ 7.4	$ 6.4	Yes
10	F	6	$ 4.0	$ 7.4	No

Figure A.3: Adaptive OFAT process exploring the combinatorial space for the best combination of design elements and management decision rules under demand scenario 4. The dollar figures are in millions.

Table A.4: Best operating plan selected for demand scenario 4.

DEs and Management DRs	Description	Best Operating Plan for Scenario 4
A	Expansion allowed in years 1-4	Yes
B	Expansion allowed in years 9-12	Yes
C	Expansion allowed in years 17-20	Yes
D	Expansion decision rule (years)	2
E	Number of floors expanded by	1
F	Number of initial floors	4

Creating Operating Plan 5

Experiment	DE and Management DR changed	Level changed to:	Output = NPV	Best output before step	Keep change?
1 (baseline)			$ 0.3		
2	C	No	$ 0.3	$ 0.3	No
3	B	No	$ 0.3	$ 0.3	No
4	D	3	$ 0.5	$ 0.3	Yes
5	D	4	$ 1.3	$ 0.5	Yes
6	F	4	$ 2.6	$ 1.3	Yes
7	F	6	$ - 3.5	$ 2.6	No
8	E	2	$ 2.2	$ 2.6	No
9	E	3	$ - 1.3	$ 2.6	No
10	A	No	$ 2.6	$ 2.6	No

Figure A.4: Adaptive OFAT process exploring the combinatorial space for the best combination of design elements and management decision rules under demand scenario 5. The dollar figures are in millions.

Table A.5: Best operating plan selected for demand scenario 5.

DEs and Management DRs	Description	Best Operating Plan for Scenario 5
A	Expansion allowed in years 1-4	Yes
B	Expansion allowed in years 9-12	Yes
C	Expansion allowed in years 17-20	Yes
D	Expansion decision rule (years)	4
E	Number of floors expanded by	1
F	Number of initial floors	4

Catalog Obtained with Different Baseline Experiments and OFAT Sequences

Results from the adaptive OFAT analysis are shown in this section in the case where different baseline experiments and OFAT sequences are chosen. The baseline experiments and OFAT sequences for the first experiments of Section 4.1.4 are shown in Table A.1. Those for the new experiments are presented in Table A.6. The catalog of operating plan resulting from this analysis is shown in Table A.7.

Table A.6: Summary of the baseline experiments and OFAT sequences used in the new set of adaptive OFAT experiments presented here.

NEW EXPERIMENTS									
Scenario 1		Scenario 2		Scenario 3		Scenario 4		Scenario 5	
Baseline Exp.	OFAT Seq.	Baseline Exp.	OFAT Seq.	Baseline Exp.	OFAT Seq.	Baseline Exp.	OFAT Seq.	Baseline Exp.	OFAT Seq.
No	E	No	D	Yes	F	Yes	C	No	B
No	F	Yes	C	Yes	B	Yes	B	Yes	A
No	B	No	F	No	D	No	F	Yes	D
3	D	2	B	2	C	3	A	4	C
3	C	3	A	2	E	1	D	3	F
6	A	4	E	4	A	6	E	4	E

Table A.7: Catalog of operating plans obtained from the analysis of five demand scenarios under the adaptive OFAT algorithm in the case where baseline experiments and OFAT sequences are chosen randomly. Each plan is associated to its corresponding demand scenario in Figure 4.5. "DE" means design element, and "DR" means decision rule.

DEs and Management DRs	Description	Op. Plan 1	Op. Plan 2	Op. Plan 3	Op. Plan 4	Op. Plan 5
A	Expansion allowed in years 1-4	Yes	Yes	Yes	Yes	No
B	Expansion allowed in years 9-12	No	Yes	Yes	Yes	Yes
C	Expansion allowed in years 17-20	No	No	No	No	Yes
D	Expansion decision rule (years)	3	2	2	2	4
E	Number of floors expanded by	2	2	2	1	1
F	Number of initial floors	6	6	4	4	4

Assessing the value of this catalog of operating plan using two thousand Monte Carlo simulations of demand scenarios, as done in step 5 of the analysis methodology, produces results shown in Table A.8. The corresponding VARG curve is shown in Figure A.5.

Table A.8: Summary of results comparing valuation attributes between an inflexible parking garage design with five initial floors, and a flexible design with a catalog of five operating plans. In the latter case, each of the two thousand Monte Carlo simulations are categorized and assigned one of five operating plans. Also, the catalog of operating plans in this case is found by generating baseline experiments and OFAT sequences randomly.

	Inflexible Design	Flexible Design with Catalog of Operating Plans	Which is Better?
Expected initial investment	$ 18.1	$ 15.5	Flex. and Catalog Better
Expected NPV	$ 2.9	$ 5.1	Flex. and Catalog Better
Expected NPV minus expected cost of flexibility	$ 2.9	$ 4.3	Flex. and Catalog Better
Minimum NPV	$ -19.5	$ -15.6	Flex. and Catalog Better
Maximum NPV	$ 8.3	$ 17.3	Flex. and Catalog Better
Value of catalog of flexible operating plans	$ 0.0	$ 1.4	

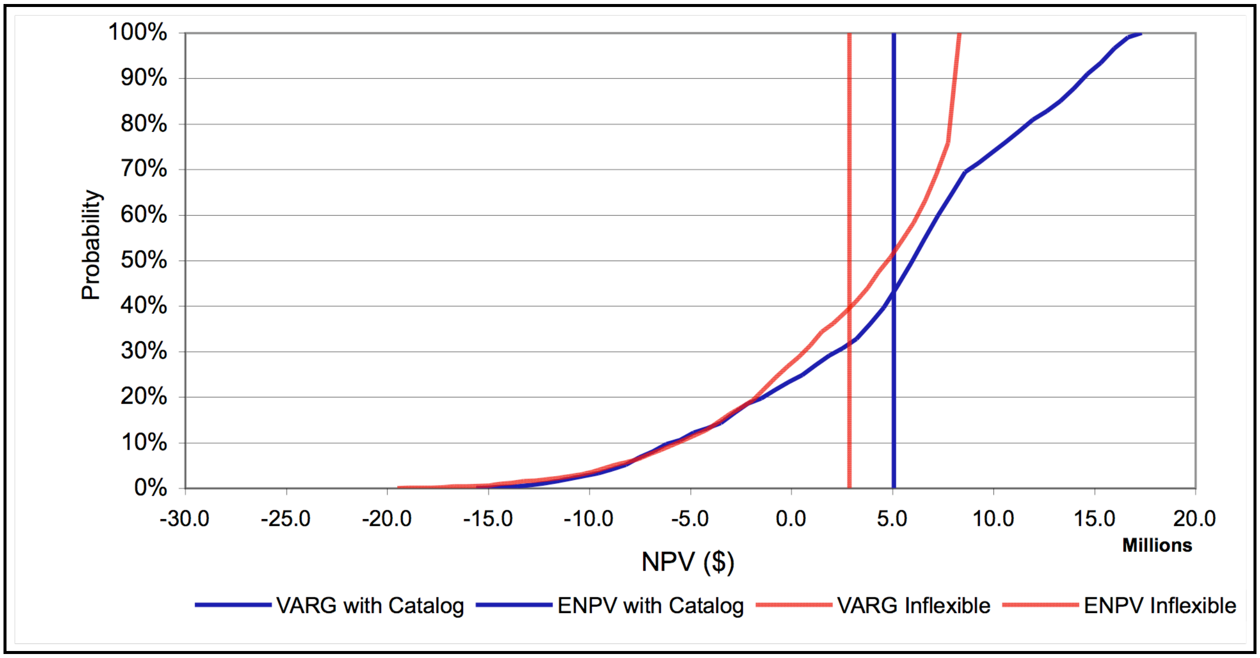

Figure A.5: VARG curves resulting from Monte Carlo simulations for both the inflexible parking garage design with five initial floors, and flexible design using a catalog of five operating plans. ENPVs for both cases are also shown. Again, these results are using randomly generated baseline experiments and OFAT sequences.

Adaptive OFAT Results for the Real Estate Development Case

Creating the Catalog of Operating Plans

This section presents the remainder of the adaptive OFAT analysis performed in step 4 of the analysis methodology to create the catalog of operating plans presented in Table 4.11. All demand scenarios used for this analysis are shown in Figure 4.15.

The chosen baseline experiment and OFAT sequence for each scenario is shown in Table A.9. For each operating plan, application of the adaptive OFAT process is shown, as well as the best operating plan emerging from this process.

Table A.9: Baseline experiments and OFAT sequences used to explore the combinatorial space for market value scenarios 1, 2, and 3, as presented in the first experiments of Section 4.2.4. Note that for market value scenario 2 the decision rule B is skipped in the adaptive OFAT sequence because it forces an operating plan similar to operating plan 3 (no investment at all). Program managers are interested in an operating plan that is an intermediate solution between operating plans 1 and 3, which justifies skipping the decision rule in the process.

FIRST EXPERIMENTS

Scenario 1		Scenario 2		Scenario 3	
Baseline Experiment	OFAT Sequence	Baseline Experiment	OFAT Sequence	Baseline Experiment	OFAT Sequence
Rule 2	A	Rule 1	A	Rule 2	B
10%	C	10%	C	10%	A
5	B	200%	B skipped	5	C

Creating Operating Plan 2

Experiment	DE and Management DR changed	Level changed to:	Output = NPV	Best output before step	Keep change?
1 (baseline)			$ -24.9		
2	A	Rule 2	$ -24.2	$ -24.9	Yes
3	A	Rule 3	$ -24.9	$ -24.2	No
4	C	1	$ -24.2	$ -24.2	No
5	C	5	$ -23.8	$ -24.2	Yes

Figure A.6: Adaptive OFAT process exploring the combinatorial space for the best combinations of levels under market value scenario 2.

Table A.10: Best operating plan selected for market value scenario 2. Management decision rules (a) are associated with a development plan (b) to form a complete operating plan.

DEs and Management DRs	Description	Best Operating Plan for Pattern 2
A	Abandonment option	Rule 2
B	Value over cost criterion for expanding	10.00%
C	Number of phases for developing the park	5

(a)

Op. Plan	Year		2007	2008	2009	2010	2011	2012	2013	2014	2015
2	Phase I	Develop? Abandon? Wait?	Develop								
	Phase II	Develop? Abandon? Wait?		Develop							
	Phase III	Develop? Abandon? Wait?			Develop						
	Phase IV	Develop? Abandon? Wait?				Wait	Wait	Abandon			
	Phase V	Develop? Abandon? Wait?					Wait	Abandon			

(b)

Creating Operating Plan 3

Experiment	DE and Management DR changed	Level changed to:	Output = NPV	Best output before step	Keep change?
1 (baseline)			$ 0.0		
2	B	50%	$ 0.0	$ 0.0	No
3	B	100%	$ 0.0	$ 0.0	No
4	A	Rule 1	$ 0.0	$ 0.0	No
5	A	Rule 3	$ 0.0	$ 0.0	No
6	C	1	$ 0.0	$ 0.0	No
7	C	2	$ 0.0	$ 0.0	No

Figure A.7: Adaptive OFAT process exploring the combinatorial space for the best combinations of levels under market value scenario 3.

Table A.11: Best operating plan selected for market value scenario 3. Management decision rules (a) are associated with a development plan (b) to form a complete operating plan. In this case, the decision rules are not relevant because no investment occurs.

DEs and Management DRs	Description	Best Operating Plan for Pattern 3
A	Abandonment option	Rule 2
B	Value over cost criterion for expanding	10.00%
C	Number of phases for developing the park	5

(a)

Op. Plan	Year		2007	2008	2009	2010	2011	2012	2013	2014	2015
3	Phase I	Develop? Abandon? Wait?	Wait	Wait	Wait	Wait	Wait	Wait	Wait	Wait	Wait
	Phase II	Develop? Abandon? Wait?		Wait	Wait	Wait	Wait	Wait	Wait	Wait	Wait
	Phase III	Develop? Abandon? Wait?			Wait	Wait	Wait	Wait	Wait	Wait	Wait
	Phase IV	Develop? Abandon? Wait?				Wait	Wait	Wait	Wait	Wait	Wait
	Phase V	Develop? Abandon? Wait?					Wait	Wait	Wait	Wait	Wait

(b)

Catalog Obtained with Different Baseline Experiments and OFAT Sequences

Results from the adaptive OFAT analysis are shown in this section in the case where different baseline experiments and OFAT sequences are chosen. The baseline experiments and OFAT sequences for the first experiments of Section 4.2.4 are shown in Table A.9. Those for the new experiments are presented in Table A.12. The catalog of operating plan resulting from this analysis is shown in Table A.13.

Table A.12: Summary of the baseline experiments and OFAT sequences used in the new set of adaptive OFAT experiments presented here.

NEW EXPERIMENTS					
Scenario 1		Scenario 2		Scenario 3	
Baseline Experiment	OFAT Sequence	Baseline Experiment	OFAT Sequence	Baseline Experiment	OFAT Sequence
Rule 2	C	Rule 3	C	Rule 2	A
10%	A	10%	A	10%	B
1	B	5	B skipped	1	C

Table A.13: Catalog of operating plans obtained from the analysis of three market value scenarios under the adaptive OFAT algorithm with different baseline experiments and OFAT sequences than those presented in Section 4.2.4. Management decision rules for each operating plan (a) are associated with a development plan (b) to form a complete operating plan.

DEs and Management DRs	Description	Op. Plan 1	Op. Plan 2	Op. Plan 3
A	Abandonment option	Rule 2	Rule 2	Rule 2
B	Value over cost criterion for expanding	10%	10%	10%
C	Number of phases for developing the park	1	5	1

(a)

Op. Plan	Year		2007	2008	2009	2010	2011	2012	2013	2014	2015
1	Phase I	Develop? Abandon? Wait?	Develop								
	Phase II	Develop? Abandon? Wait?		Develop							
	Phase III	Develop? Abandon? Wait?			Develop						
	Phase IV	Develop? Abandon? Wait?				Develop					
	Phase V	Develop? Abandon? Wait?					Develop				
2											
	Phase I	Develop? Abandon? Wait?	Develop								
	Phase II	Develop? Abandon? Wait?		Develop							
	Phase III	Develop? Abandon? Wait?			Develop						
	Phase IV	Develop? Abandon? Wait?				Wait	Wait	Abandon			
	Phase V	Develop? Abandon? Wait?					Wait	Abandon			
3											
	Phase I	Develop? Abandon? Wait?	Wait	Wait	Wait	Wait	Wait	Wait	Wait	Wait	Wait
	Phase II	Develop? Abandon? Wait?		Wait	Wait	Wait	Wait	Wait	Wait	Wait	Wait
	Phase III	Develop? Abandon? Wait?			Wait	Wait	Wait	Wait	Wait	Wait	Wait
	Phase IV	Develop? Abandon? Wait?				Wait	Wait	Wait	Wait	Wait	Wait
	Phase V	Develop? Abandon? Wait?					Wait	Wait	Wait	Wait	Wait

(b)

Assessing the value of this catalog of operating plan using two thousand Monte Carlo simulations of demand scenarios, as done in step 5 of the analysis methodology, produces results shown in Table A.14. The corresponding VARG curve is shown in Figure A.8.

Table A.14: Summary of results comparing valuation attributes between an inflexible real estate development project with all phases developed in a row, and a flexible design with a catalog of three operating plans. In the latter case, each of the two thousand Monte Carlo simulations are categorized and assigned one of three operating plans. This is the case where new experiments are done, as compared to the first set of experiments presented in Section 4.2.4.

	Inflexible Design	Flexible Design with Catalog of Operating Plans	Which is Better?
Initial investment	$ 27.3	$ 21.4	Flex. and Catalog Better
Expected NPV	$ 3.3	$ 16.3	Flex. and Catalog Better
Minimum NPV	$ -59.2	$ -25.3	Flex. and Catalog Better
Maximum NPV	$ 77.9	$ 100.7	Flex. and Catalog Better
Value of Flexibility	$ 0.0	$ 13.0	

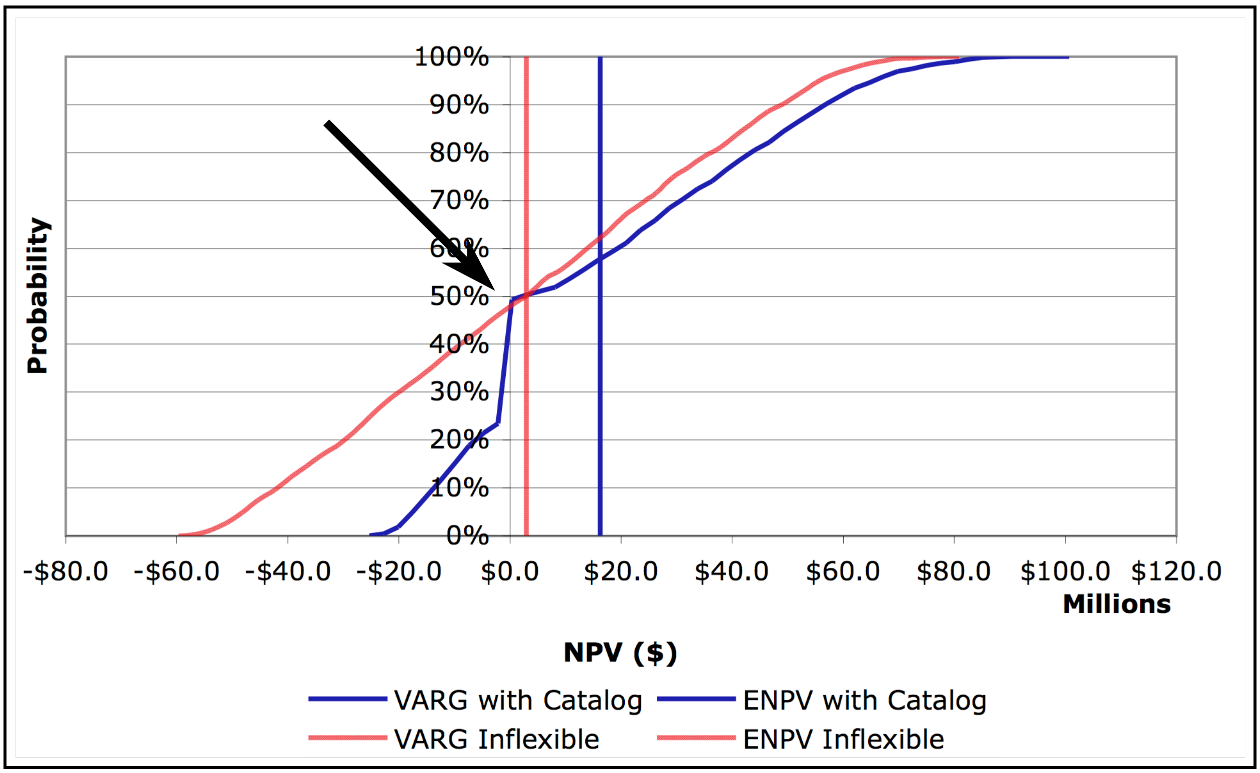

Figure A.8: VARG curves and ENPVs resulting from Monte Carlo simulations for both the inflexible real estate development with all phases developed in a row, and flexible design using a catalog of three operating plans. This is the case where new experiments are done, as compared to the first set of experiments presented in Section 4.2.4. The arrow points out an interesting feature of the VARG curves, where NPVs for the case with the catalog of

operating plans are lower than those produced by the inflexible case (around 50% cumulative probability). This is due to the flexibility of abandoning the project if market conditions are unfavorable right at the outset, and to the cost of acquiring the flexibility when market conditions are barely favorable for development.