Design Catalogs: A Systematic Approach to Design and Value Flexibility in Engineering Systems

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Abstract

This paper proposes *design catalogs* as an efficient systematic process for identifying and evaluating improved designs in engineering systems by exploiting ideas of flexibility. Standard design and evaluation approaches typically do not cope well with a range of possible operating conditions. They often simplify considerations of uncertainty, which may lead to designs that do not perform as well as those responding dynamically to changing conditions. The proposed process addresses the complexity of the design problem under uncertainty, recognizing that it is impossible to analyze all possible combinations of evolutions, and the flexible ways in which the system could adapt over time. The process creates a small subset of designs that collectively perform well over a range of scenarios. It bundles representative scenarios and their flexible responses to enable a more thorough analysis that accounts explicitly for uncertainty – and enable considerations of improved designs. Each element consists of combinations of design variables, parameters, and management decision rules carefully selected, and referred as operating plans. In the example analysis, the process improves economic performance by 37% as compared to standard methods in an infrastructure system case study, while exploring only 3% of the design space. It reaches 88% of the stochastically optimal solution while being 183 times faster computationally in the example numerical study. The systematic property aims for practical applications in industry. In each phase, it gives the freedom to rely on the designer's expertise with the system, or to consider analytical tools already in use at the design organization.

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1 Introduction

Engineering systems are characterized by a high degree of technical complexity, social intricacy, and elaborate processes aimed at fulfilling important functions in society [ESD, 2011]. Given they are long-lived, they face much uncertainty at strategic, tactical, and operational levels. Infrastructure systems are a particular class of engineering systems that serve an important role in any modern city, supporting emergency services (e.g. ambulance stations, hospitals), power generation and distribution (e.g. power plants and national grid), telecommunications (e.g. cell phone network), transportation (e.g. airports, roads, bridges, highways), and housing activities (e.g. real estate developments). Infrastructure systems are the focus of this paper.

The early phase of design decision-making for engineering systems is a daunting task. Fig. 1 illustrates various phases of the standard design and evaluation process. Those are typically considered of the conceptual design and architecture activities occurring in the system development phase, before a more detailed design phase in systems engineering [INCOSE, 2015]. It starts from an initial design, then recognizes the main uncertainty drivers affecting lifecycle performance, recognizes that managers will adjust the system over time in an effort to accommodate changing conditions, and relies on various metrics to assess economic (e.g. net present value or NPV) and/or non-economic performance (e.g. response time for emergency services). Such process involves modeling and optimization of basic infrastructure designs (e.g. plants, networks, etc.) considering several possible design alternatives in phase 1, and considerations of uncertainty scenarios (e.g. market demand, price, regulations) over long-term horizons in phase 2. There can be many architectures and operating modes possible (e.g. number and size of plants, routing of vehicles on road network, etc.), as recognized in phase 3. The system can also be evaluated based on many lifecycle performance metrics (e.g. internal rate of return (IRR), NPV, return on investment (ROI), etc.) as captured in phase 4. Analyzing the full problem is typically intractable, as all possible design combinations and alternatives cannot be analyzed exhaustively.

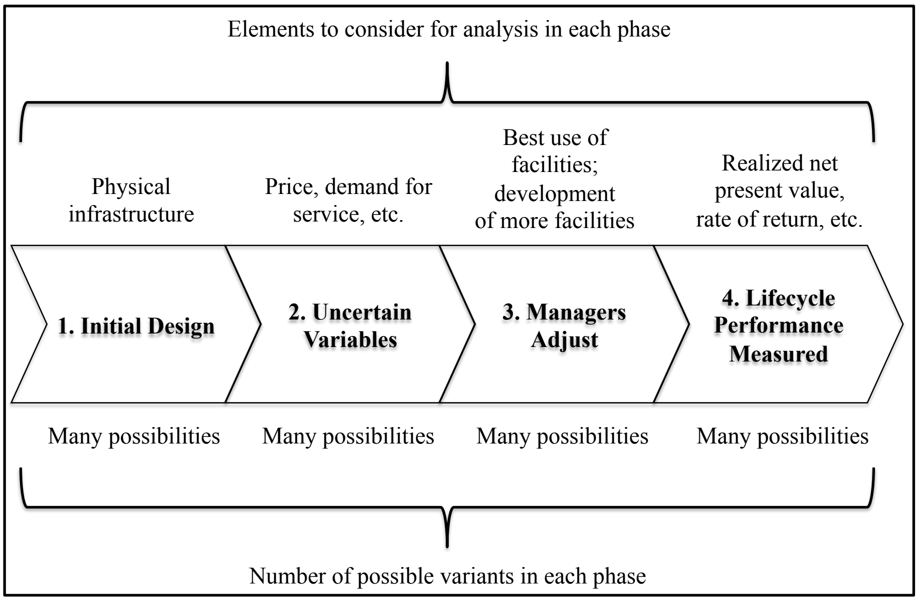

Fig. 1. Full analytical problem for designing engineering systems as part of conceptual design activities.

A typical approach in systems design and analysis is to simplify the full analytical problem to make it more tractable. Instead of considering many scenarios of periodical data, designs are often optimized for the most likely projection of the major uncertainty drivers [de Neufville and Scholtes, 2011]. Typical project evaluation approaches based on discounted cash flow (DCF) analysis, such as NPV, do not account well for the fact that managers will react periodically to enhance system performance [Trigeorgis, 1996]. Also, design decisions are often based on one evaluation metric like IRR, ROI or NPV. Such practices can lead to sub-optimal design selection, or leaving aside altogether potential solutions that could offer better lifecycle performance.

There has been a great deal of effort over the last two decades to improve standard design and project evaluation practice by making more explicit considerations of uncertainty and flexibility in engineering systems design. Flexibility enables a system to change and adapt pro-actively to changing environments, markets, regulations, and technology [de Neufville and Scholtes, 2011]. It improves expected lifecycle performance by affecting the distribution of possible outcomes, selecting designs that reduce the effect from downside conditions (i.e. like buying insurance) while enabling the system to capitalize on favorable opportunities (i.e. like buying a call option on a stock). A flexible systems design concept is composed of a) a strategy (e.g. abandon the system permanently or temporarily, expand capacity, switch design configurations to provide better redundancy, etc.) to handle uncertainty, akin to a real option "on" the system, and b) an enabler in design and management, akin to a real option "in" the system [Cardin, 2014]. Several studies have shown improvements ranging between 10-30% compared to the outcome from standard design and evaluation practice, in line with traditional ROA evaluation. These cover a wide range of industries: space systems and telecommunications [Silver and de Weck, 2007, Nilchiani and Hastings, 2007, de Weck, de Neufville and Chaize, 2004], defense [Mikaelian, Nightingale, Rhodes and Hastings, 2011], water infrastructures [Zhang and Babovic, 2011], etc.[2]

The 25 de Abril bridge connecting Lisbon to the municipality of Almada in Portugal is a real-world example of flexible thinking in engineering design. It was originally designed to carry four car lanes, but engineers accommodated the design for more lanes if needed in the future, as well as a railway on its lower platform, should usage and demographic patterns warrant it. This flexible design later allowed expansion to the current six car lanes and two-railroad tracks infrastructure that exists today. This strategy required a smaller initial investment than if full capacity had been deployed, and deferred additional costs to the future, taking advantage of the time-value of money by lowering their economic net present value. It also enabled more traffic between the two cities today, contributing to a growing economy.

An important issue in analyzing infrastructure systems for flexibility is the complexity of the analytical problem. In addition to the many physical design variables and parameters, designers should account for a wide range of uncertainty scenarios, periodic managerial adjustments, and evaluation metrics. Additional variables (e.g.

[2] More case studies are available: http://ardent.mit.edu/real_options/Common_course_materials/papers.html, http://strategic.mit.edu/publications.php, http://seari.mit.edu/publications.php, and http://www.ise.nus.edu.sg/staff/cardin/publications.html

uncertainty drivers, flexibility decision rules[3]) need to be introduced in the analytical problem, which increases computational complexity. Standard approaches to value flexibility based on real options analysis (ROA) may not be suitable for such problem in an engineering setting, as discussed below.

The problem addressed in this paper is that the analysis of performance of an engineering system under uncertainty is not easy, and may even be intractable from an analytical standpoint if many design variables and scenarios are considered. Consideration of flexibility to adapt to changing conditions exacerbates this problem. Hence, there is a need to develop and evaluate a new practical approach to facilitate this analysis in an engineering setting.

The main research question addressed here is: "What structured process can be devised to enable an extended analysis of the design of engineering systems with explicit considerations of uncertainty and flexibility, while improving lifecycle performance and being tractable analytically as compared to standard design and evaluation approaches?" A secondary question is: "What is the lifecycle performance improvement brought by the proposed mechanism when applied to the analysis of an example engineering system, and how does it compare to other competing methods?"

1.1 Proposed Solution

The proposed solution relies on the concept of *design catalog*. The catalog consists of a set of *operating plans* bundling flexible design architectures and managerial responses intended to suit relevant uncertainty patterns designers might wish to anticipate. An operating plan is therefore a combination of design variables, parameters, and flexible decision rules to manage the infrastructure system in operations, and over its lifecycle. One flexible operating plan is created to suit each scenario, thereby creating the catalog. In the evaluation phase, a wide range of uncertainty scenarios is simulated, and one operating plan may be assigned to each scenario to determine how the system will perform. Lifecycle performance is then measured along different metrics (e.g. ROI, NPV, IRR) to accommodate different risk profiles in decision-making.

Illustrating the concept using a hypothetical example based on the 25 de Abril bridge case, an operating plan could have been to design an initial number of lanes with the possibility to expand in the future – as done by the system architect(s). To account for flexibility decision rules, the bridge capacity could have been expanded when vehicle usage exceeded a particular decision-making threshold T for several consecutive years. Different capacity usage scenarios could have been considered upfront (e.g. low, medium, high) and a contingency or operating plan could have been devised depending on how this uncertainty driver evolves, changing the timing and size of the expansion based on the actual scenario occurring. Such plans could have been used in the upfront evaluation of the design project.

[3] A decision rule is akin to an "if" statement, or "trigger mechanism" based on observations of the uncertainty drivers, determining when it is appropriate to exercise a given flexibility.

This design catalog proposed here is devised by selecting a set of operating plans or models that together deal reasonably well over a certain range of uncertainty scenarios. This speeds up the analysis for the most relevant plans, allows analysts to consider more design alternatives, and enables uncovering better design solutions with improved lifecycle performance without relying on more advanced methods based on stochastic programming or simulation-based optimization. The proposed solution suggests a middle ground between the simplest set of assumptions typically made in design and evaluation, and the full analytical problem depicted Fig. 1. It focuses on uncertainty sources that are known to system designers and can be characterized probabilistically (e.g. market demand, prices, regulatory changes, etc.) It relies on a range of possible scenarios small enough to be manageable analytically, but broad enough to enable better-informed design decisions. The aim is to provide a practical approach leading analysts to rapid lifecycle performance improvements by explicit considerations of flexibility, while limiting the computational overhead associated with a more advanced analysis.

The remainder of the paper is organized as follows. In Section 2 a review of related work highlights previous efforts to generate and value flexibility in engineering systems design. Section 3 explains the process of constructing and evaluating the design catalog. Section 4 presents an example application of the proposed process in the analysis of an example infrastructure system. It also compares with other advanced methods based on simulation-based optimization. Results, findings, validity, and limitations of the results are discussed in Section 5, together with possible avenues for future work, followed by conclusions in Section 6.

2 Related Work

2.1 Valuing Flexibility in Engineering Design

Enabling flexibility in engineering design essentially involves five phases: 1) standard/baseline design, 2) uncertainty recognition, 3) concept generation, 4) design space exploration, and 5) process management [Cardin, 2014]. Several procedures exist to support architecture and design activities in each phase. In phase 1, Tomiyama et al. [2009] describe procedures to help generate an initial/baseline design (e.g. axiomatic design, TRIZ). In phase 2, procedures like scenario planning and binomial lattice are used to characterize and model uncertainty, as summarized by de Weck et al. [2007]. In phase 3, flexible systems design concepts are generated to address the main uncertainty drivers identified in phase 2, as explained by Cardin et al. [2013] and done in the studies by Mikaelian et al. [2012, 2011]. In phase 4, the preferred design configuration is identified relying on real options, optimization, and statistical techniques, as explained by de Neufville and Scholtes [2011]. Phase 5 ties in all the previous phases, joining all relevant stakeholders in the process of generating, designing, implementing, and managing flexibility in operations. Game theory and simulation games can be used to better understand the conditions favorable to good process management, as done by Smit [2001] and Cardin et al. [2015].

This section summarizes the latest efforts to develop practical approaches to value flexibility in engineering systems design (i.e. focusing on phase 4 from above). Interested readers will find more details on each procedure, as well as an analysis of their individual strengths and weaknesses in Cardin [2014]. The evaluation effort involves two streams. The first stream focuses on developing techniques for valuing flexibility in an engineering context. Traditionally, flexibility has been valued using ROA techniques inspired from financial options analysis. ROA relies on the Black-Scholes formula [Black and Scholes, 1973], binomial lattice [Cox, Ross and Rubinstein, 1979], ordinary differential equations, and/or dynamic programming techniques [Trigeorgis, 1996]. Such techniques, however, are based on assumptions that may not hold in an engineering context. For example, ROA based on arbitrage-enforced pricing assumes that markets of comparable tradable assets exist, are complete, and frictionless. This enables constructing a replicating portfolio that hedges perfectly the cash flows produced by the asset, and helps to quantify the value of flexibility. Such markets and ideal conditions may not exist for new engineering projects. Also, the path independence assumption inherent to recombining binomial lattice may not reflect well the realities of a new engineering project. An up-down movement in demand or price, for instance, may lead to a different sequence of engineering decisions (e.g. build, not build) than for a down-up movement over two periods.

More recently, novel techniques relaxing the constraints imposed by economic theory have been proposed to suit the needs of flexibility analysis in engineering design. These involve mainly decision analysis, lattice analysis, and Monte Carlo simulation [Cardin, 2014]. Decision analysis and lattice analysis are simplified versions of standard ROA techniques relying on dynamic programming. Monte Carlo simulation as proposed by de Neufville and Scholtes [2011] exploits the idea of decision rule, which departs significantly from traditional methods to value flexibility, and is crucial to the approach proposed here.

The concept of decision rule defines a trigger point or mechanism at which time it is appropriate to exercise a given flexibility. It simulates an appropriate decision taken by the system operator or manager at any point in time to adapt the system to changing conditions. Such rule is typically based on the observation or forecast of an uncertainty driver to which the system is called to react. In the example of the 25 de Abril bridge, a decision rule could be that if traffic demand reached the threshold T, additional lanes would be added. If traffic demand increased even further, this would warrant development of the railroads on the lower platform. While it is unclear what decision rule was used in this historical case, it is clear that the decision to expand capacity was based on observed changes in the main uncertainty drivers (e.g. availability of EU funds, possible land boom on South shore, etc.)

2.2 Computationally Efficient Techniques

The second stream involves developing computationally efficient techniques to identify the most valuable flexible systems design concepts, subject to a range of design variables, parameters, decision rules, and uncertainty scenarios. For example, flexible capacity expansion in the 25 de Abril bridge case could give rise to a range of flexible design alternatives with different decision rules. Designs could account for one, two, or three extra lanes when user demand reaches threshold T, account for one or two additional rail tracks, etc. Given T alone can take on any values, the number of possible solutions is infinite, each leading to a different lifecycle performance outcome.

Most efforts have involved combining flexibility valuation tools with deterministic optimizations, stochastic programming, simulation-based optimization, and statistical techniques to reduce computational overhead. de

Neufville and Scholtes [2011] refers to them as screening methods, and suggested three types: bottom-up, simulators, and top-down. Bottom-up models use simplified versions of a complex, detailed design model. Simulators incorporate statistical techniques (e.g. surrogate response surface modeling) and/or fundamental principles to mimic the response of the detailed model. Top-down models use representations of major relationships between the parts of the system to understand possible system responses (e.g. systems dynamics). Stochastic programming, simulation-based optimization, and/or meta-modeling techniques – e.g. [Kall and Wallace, 1994, Romero, Amon and Finger, 2012] – can also be used to tackle engineering systems design problems. On the other hand, these require more advanced techniques imposing additional burden to the analyst, and little work has been done in these areas related to flexibility analysis. The studies below are few of the latest efforts.

Wang [2005] was first to apply screening methods to the flexibility analysis of water infrastructures in China. Lin et al. [2013] used a bottom-up screening model approach to identify valuable flexible design alternatives in an offshore oilrig system. Ranjbar et al. [2013] proposed an integrated screening framework based on Kriging to speed up the analysis. Yang [2009] used a response-surface methodology coupled with fractional factorial analysis to explore flexibility in the car manufacturing process. Ross [2006] proposed Multi-Attribute Trade space Exploration (MATE) based on Pareto-optimal configurations to exploit tradeoffs between design performance utility attributes, and lifecycle cost.

2.3 Contributions

An novel approach must be devised to enable practical and efficient analysis of uncertainty and flexibility in the design of engineering systems. Traditional ROA methods are often criticized for requiring too advanced mathematical techniques, and for relying on assumptions that are not realistic in an engineering setting. This may have slowed down their adoption in academic circles and in industry practice. Designing and valuing flexibility exacerbates the analytical problem since it requires considerations of several uncertainty scenarios and decision rules, in addition to the already considerably large space of architectural design variable and parameters. While screening, stochastic programming, and simulation-based optimization methods can be used, they can be difficult to use in practice due to the advanced level of mathematical training required. There is a need for a new approach suitable for engineering, practical, systematic, and reducing the computational overhead as compared to more advanced techniques.

The process detailed in the next section introduces a practical approach to expand treatment of the analytical problem described in Fig. 1. It relies on a simulation approach to flexibility valuation, which may be more intuitive to systems engineers and practitioners since it relies on an extension of existing techniques for project evaluation and design. It is more suitable for an engineering setting because it does not depend on several of the economic assumptions inherent to standard ROA. The process relies on a computationally efficient algorithm for exploring the design space systematically, and does not require advanced optimization and stochastic programming techniques. It enables the creation of a design catalog consisting of several operating plans that adjust the response based on uncertainty realizations. It enables the analyst to consider uncertainty and flexibility explicitly, while not requiring use of more advanced mathematical techniques as necessary to conduct standard ROA.

3 Design Catalog Process

Fig. 2 summarizes the proposed catalog-based process, which consists of five steps that build upon and extend the process described in Fig. 1: 1) develop a basic model of the system for measuring lifecycle performance, 2) find representative uncertainty scenarios affecting lifecycle performance most, 3) identify and generate potential sources of flexibility in design and management, 4) find the most appropriate flexible operating plan for each scenario and construct the design catalog, and 5) assess lifecycle performance and compare with the baseline design under uncertainty. In the description below, popular techniques used in industry and academic circles are suggested. This choice, however, ultimately rests with the organization implementing the process.

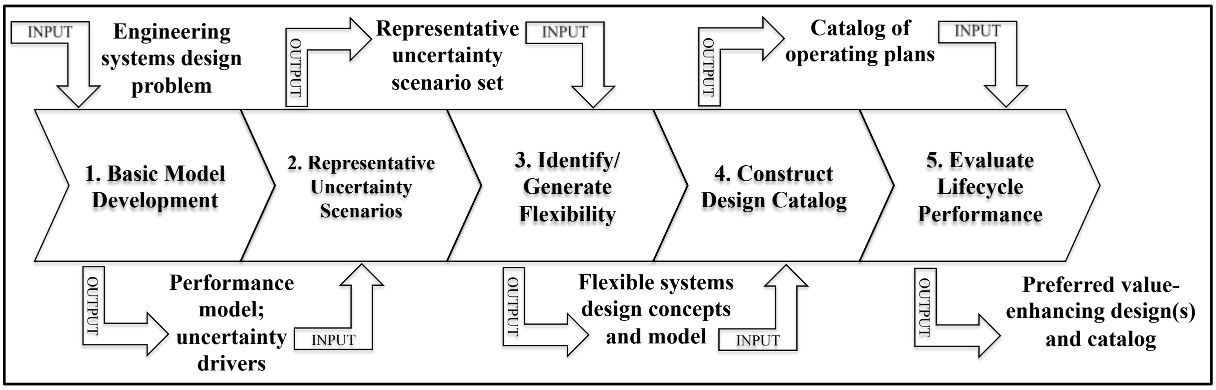

Fig. 2. A design catalog approach for designing engineering systems for flexibility.

The goal of step 1 is to develop a basic model to measure the lifecycle performance of the system under different scenarios. This step takes as input an engineering systems design problem, and outputs a performance model, alongside identified uncertainty driver(s) that is (are) most likely to affect lifecycle performance. In industry, DCF analysis is typically used to assess expected economic performance, but other modeling techniques can be used, like agent-based modeling, queuing, computer-aided design, discrete event simulations, etc. The choice of modeling approach depends on the nature of the system, the complexity, the types of measurements necessary, and the approach already in use at the organization.

The goal of step 2 is to find a set of representative scenarios capturing the range of possible uncertainty drivers affecting lifecycle performance. The input to this step is (are) the main uncertainty driver(s), modeled as part of the performance model, and the output consists of a representative set of such scenarios that are used to stimulate flexible systems design concept generation in step 3. Finding such representative set can be done using popular methods in industry like Shell scenario planning, probability elicitation, or case-based reasoning based on discussions with design experts within the design organization and/or with the client [Morgan and Henrion, 1990, Helmer-Hirschberg, 1967, Schoemaker, 1995, Reich and Kapeliuk, 2004]. Here, a systematic process based on scenario planning is proposed – see Appendix for suggested elicitation items. Originally developed and used at Shell, this modified process involves a) defining the scope of the problem, b) identifying major stakeholders, c) identifying basic trends, d) identifying key uncertainties, e) constructing initial scenario themes, f) developing quantitative models, and h) evolving towards decision-making. Enough scenarios must be selected to capture the nature of the variations, and spectrum of possible outcomes (e.g. 5-15 scenarios). Not too many scenarios must be chosen to avoid the computational burden typically associated to simulation-based and stochastic programming techniques. This step borrows conceptually from the sampled average approximation technique used in stochastic programming. It aims to reduce the number of scenarios considered for optimization, and thus the computational burden.

The goal of step 3 is to generate flexible systems design concepts. The input to this step is the set of representative uncertainty scenarios. The output is (are) the flexible systems design concepts and augmented model to be used in step 4 to construct the catalog of operating plans. This step is the subject of active ongoing research to develop and evaluate procedures enabling this more systematically. Here, designers generate alternatives that aim at improving performance in the face of uncertainty by exploiting the idea of flexibility. While there is no particular method that represents best practice, several techniques based on real options analysis, prompting, brainstorming, and/or design structure matrix (DSM) have been proposed and evaluated in the literature in application domains involving complex systems like fleets of unmanned aero vehicles, real estate development projects, and waste-to-energy infrastructure systems [Mikaelian, Nightingale, Rhodes and Hastings, 2011, Mikaelian, Rhodes, Nightingale and Hastings, 2012, Cardin, et al., 2013, Hu and Cardin, 2015]. The strengths and limitations of each procedure are discussed in details in [Cardin, 2014], which help provide guidance on the appropriate procedures to choose, depending on the system and analytical context...

The goal of step 4 is to construct the design catalog. The input(s) is (are) the flexible systems design concept(s) of interest and augmented performance model, and the output is a catalog of operating plans. The preferred flexible operating plan is found for each representative scenario to model managers' ability to change operating plan as uncertainty unfolds. Each plan also models a possible flexibility strategy exploited within a given scenario. Thus, flexibility is exploited at two levels in the proposed framework: the ability to change between operating plans combined with the ability to adapt within a given operating plan. This step is similar conceptually to a discretization step often done in solving stochastic programs.

Several mechanisms can be used in step 4 to construct the catalog. The choice of algorithm depends on the nature of the design problem (e.g. discrete vs. continuous variables, linear vs. non-linear objective function, deterministic vs. stochastic). One can rely on DOE techniques such as full or fractional factorial analysis, parameter studies, one-at-a-time, latin hypercubes, or orthogonal arrays to sample the design space systematically for each operating plan [Box, Hunter and Hunter, 1978]. Meta-heuristics optimization algorithms can be used, such as genetic algorithms [Holland, 1975], simulated annealing [Kirkpatrick, Gelatt and Vecchi, 1983], and particle swarm optimization [Kennedy and Eberhard, 1995]. Linear programming, mixed integer programming, barrier methods, and/or sequential quadratic programming can also be used [Gill, Murray and Wright, 1986]. The consequences of using different algorithms may affect the quality of the solution, and/or the level of computations needed. The texts referenced provide guidance on the best algorithm to use, depending on time, problem type, and resources available to the analyst.

The goal of step 5 is to compare the results obtained using the catalog with those obtained for the basic model in step 1, to measure the improvement brought by the design catalog – if any – as compared with standard design and evaluation. This step takes as input the design catalog, and outputs a preferred set of value-enhancing flexible design(s) and catalog to be considered for the detailed analysis phase of the systems engineering process. This is done by simulating a wide range of uncertainty scenarios, assigning one operating plan to each scenario, and measuring the system performance under each plan/scenario. This step is similar to out-of-sample testing performed in stochastic programming, provided that the samples are generated from the same process or model used to generate the representative scenarios in step 2. Different performance comparisons can be made. To determine the value of flexibility both in using the catalog and the flexible operating plans, the analysis with and without the catalog can be conducted. Outcome distributions can be compared to determine how flexibility affects the proposed designs (i.e. does it protect from downside conditions, helps capitalize on upside opportunities, both?). Multi-criteria evaluation helps comparing the design alternatives or catalogs using different evaluation metric (e.g. mean performance, 5^{th} or 95^{th} percentile, etc.) to accommodate different risk profiles in decision-making.

4 Application

This section demonstrates how to apply the five-step process in the analysis of an example infrastructure system. The objectives are to address the research questions by demonstrating that the process:

1) Works for a real-world system;
2) Improves and recognizes additional value through explicit recognition of uncertainty and flexibility;
3) Provides better solutions compared to a baseline design that is typically more rigid (i.e. inflexible) representing the outcome of standard design and evaluation practice, and;
4) Reduces computational overhead significantly as compared to a full exhaustive analysis relying on simulation-based optimization.

4.1 Example Study: Infrastructure System

The case study is inspired from the development of a vertical multi-level parking garage built beside the Bluewater commercial center near London in the United Kingdom. This real infrastructure development project was launched to accommodate the parking needs of potential new customers and visitors to the mall. Since the growth in potential customers/visitors was unknown, the system designers and architects embedded flexibility in the system to accommodate extra floors and capacity, thereby providing more parking spaces in case more customers visited the mall than originally planned. de Neufville et al. [2006] used this case example to show that this strategy was worthwhile. They showed that a flexible design could create additional economic value in the face of uncertain demand growth, as opposed to a system designed with best – or stochastically optimal – fixed capacity.

In this paper, the modeling assumptions are similar to those used by de Neufville and Scholtes [2011], who developed a case example based on the Bluewater commercial center. There and in [de Neufville, Scholtes and Wang, 2006], the authors introduced the notion of a decision rule as a way to value flexibility. The authors only explored the value associated to one decision rule, however, and did not explore other combinations of decision rules and design variables, or determined the optimal parameters characterizing such rules. Application of the design catalog technique shown next enables a more thorough exploration of the design space, and demonstrates value improvement as compared to the baseline analysis based on this case study example.

4.1.1 Step 1: Basic Model Development

Application of the catalog approach starts from the development of a basic quantitative model enabling lifecycle performance assessment of design alternatives. Here, an economic DCF model is used, inspired from the data reported in de Neufville and Scholtes [2011], and summarized in Appendix (Table 11). NPV is the objective function (O) for measuring performance of different alternatives. The model implements the following relationships between the design variables (DV), design parameters (DP), and constraints (C):

$$NPV = \sum_{t=0}^{T} \frac{R_t - C_t}{(1+r)^t} \qquad (1)$$

$$R_t = \min(D_t, k_t)p,\ t \geq 0 \qquad (2)$$

$$k_t = n_0 \sum_{t=0}^{T} f_t \qquad (3)$$

$$k_t \leq n_0 f_{max},\ t \geq 0 \qquad (4)$$

$$C_0 = cc_0 + c_f + c_l \qquad (5)$$

$$C_t = k_t c_r + c_l + c_e,\ t > 0 \qquad (6)$$

$$D_t = D_f - \alpha e^{-\beta t} \qquad (7)$$

Equation 1 shows how to compute NPV, which is a standard DCF analysis. Equation 2 states that revenues in any given year t are capped by installed capacity k_t at time t. Equation 3 constrains installed capacity k_t to be the sum of parking spaces built in each previous years, plus the number of floors f_t added at time t. In the inflexible system, $k_0 = n_0 f_0$, the initial capacity of the system, and $f_t = 0\ \forall\ t$, since no expansion is possible. For the flexible system, $f_t \neq 0$ because expansion occurs as demand changes. Equation 4 explains that the total number of floors is capped at f_{max} such that k_t in any given year does not go beyond $n_0 f_{max}$. Equation 5 shows that cost at year 0 (C_0) is given by the total construction cost cc_0, the cost of acquiring the flexibility to expand[4] c_f (i.e. stronger

[4] Variable $c_f = 0$ for simplification only. The model is used to assess the value of flexibility assuming that flexibility is already available. The real value of a design thus takes the measured NPV and subtracts from it the real acquisition cost of the flexibility. As long as this difference is positive (i.e. NPV – c_f (real) > 0), flexibility is worth embedding in the design.

columns to support expansion, as described below), and the cost of leasing land c_l. The total construction cost is $cc_0 = n_0 f_0 c_c$ for the first two floors, and then grows at rate $g_c = 10\%$ for all floors above. Equation 6 shows that total cost C_t includes recurring operating cost $k_t c_r$, land leasing cost c_l, and expansion cost c_e. Cost c_c is measured based on the growth in construction cost g_C times the number of additional parking space built at time t.

Deterministic demand for parking space D_t in year t is identified as the main uncertainty driver in this system. The initial deterministic projection is modeled using Equation 7, where α = additional demand by project midlife (year 10) + additional demand by final year (year 20), β = - ln(additional demand by year 10/α) / (10 – 1), and D_f is final demand at year 20. The model assumes that D_1 = 750 parking spaces, additional demand by year 10 = 750, and additional demand by final year = 250, such that α = 1,000 and β = 0.15. Under this framework, an example design vector for the inflexible system is simply f_0, the initial number of floors. Here f_t = 0 for $\forall$ t, and therefore $k_t = k_0$. The optimal design based on deterministic optimization has six floors ($f_0^* = 6$), leading to NPV = $10.6 million.

4.1.2 Step 2: Finding Representative Uncertainty Scenarios

This step finds a representative set of scenarios for the major uncertainty sources affecting lifecycle performance. Five scenarios are identified using the process inspired from scenario planning techniques [Schoemaker, 1995] – see Appendix. Through personal communications with system experts, such process is used to a) define the scope of the problem (i.e. develop a parking garage infrastructure), b) identify major stakeholders (i.e. users, owners), c) identify basic trends (e.g. growing uncertain demand for parking space), d) identify key uncertainties (i.e. parking space demand), e) construct initial scenario themes (e.g. slow growth followed by rapid growth, rapid growth followed by slow growth, etc.), f) develop quantitative models (i.e. Equations 1-8), and h) evolve towards decision-making (i.e. used NPV as basis for decision-making).

Discussions with system experts led to a characterization of representative demand scenarios captured in Table 1. The resulting scenarios are modeled as variations of the deterministic scenario in Equation 7. In characterizing the main scenario themes, it was decided that five scenario categories would span the space of possible demand scenarios adequately. This assumption may be changed, as discussed in Section 4.2. Initial growth over the first five years is taken as the main criterion for categorizing different scenarios. Years 1-5 are crucial to development and profitability, as demand will taper off to an asymptotical value in year 20.

Table 1 Categories of representative demand scenarios based on percentage increase from years 1 to 5.

Category	Growth parameter β	Percentage increase	Mid-value
1	0.990	131%	123%
2	0.500	115%	100%
3	0.250	84%	68%
4	0.125	52%	38%
5	0.050	24%	

Representative scenarios are split into five growth categories. Five growth parameters β give rise to five representative scenarios in Fig. 3. The percentage increase over five years is calculated for each representative scenario. The mid-values provide a breaking point to assign demand scenarios to each category. For instance, scenarios with growth above mid-value 123% in years 1 to 5 are assigned to category 1, while scenarios with growth less than 38% are assigned to category 5. The approach for doing this is not unique, and may change depending on the design problem, analysts, and input assumptions.

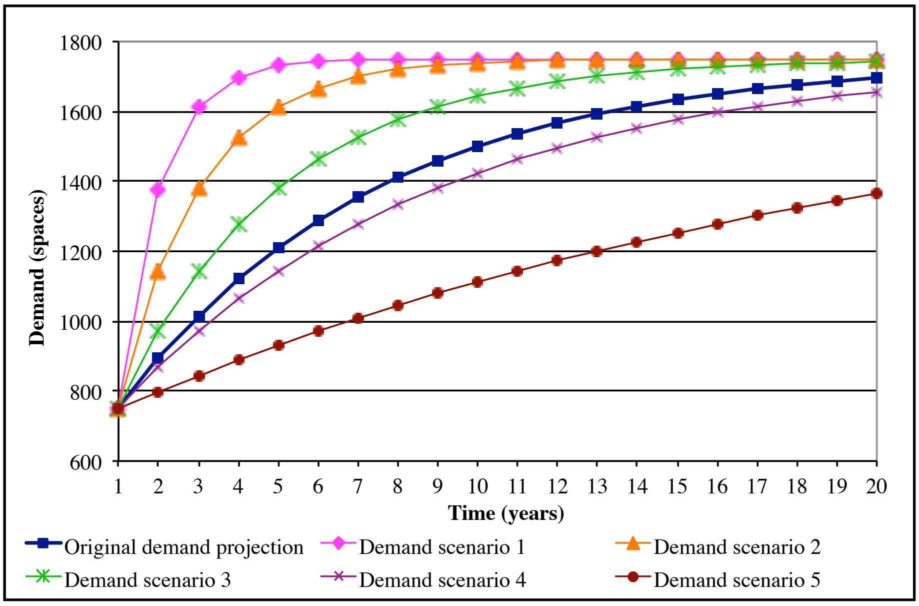

Fig. 3. Set of representative demand scenarios based on the exponential demand model with β = 0.990, 0.500, 0.250, 0.125, and 0.050.

4.1.3 Step 3: Identify/Generate Flexibility in Systems Design and Management

This step uses the prompting procedure from Cardin et al. [2013] to identify and generate flexible systems design concepts, which is available online as supplementary material to the paper. The procedure consists of a series of short questions to elicit the concepts through interactive discussions with system experts. It induces designers to identify relevant flexibility strategies, enablers, and decision rules, in light of the representative uncertainty drivers and scenarios identified in step 2.

The major opportunity for flexibility identified in this system is the ability to expand capacity as needed, in line with the work presented in de Neufville and Scholtes [2011]. The design vector is represented as: [a_{1-4}, a_{9-12}, a_{17-20}, dr, f_t, f_0]. This vector includes both decision rules and design variables. Decision rules are implemented using logical programming statements in Excel® – i.e. `IF(logical condition, outcome if true, outcome if false)`. Decision rules a_{1-4}, a_{9-12}, and a_{17-20} state respectively whether it is possible to expand capacity during years 1-4, 9-12, and/or 17-20 by taking on binary values (Yes = 1, No = 0). These rules capture the fact that it may not make sense to allow expansion in the early years of the project, or at the end. Similarly, it may be best in some cases not to allow expansion in years 9-12 to study mid-life evolution of the project. Decision rule dr specifies for how many consecutive years demand must be higher than installed capacity to allow expansion. For example, dr = 1 means that demand will be observed for just one year prior to the decision – which is suitable for more aggressive and risk-seeking decision-makers. If it is higher than installed capacity, expansion will occur, if not capacity will remain the same. Design variable f_t determines how many floors are added at each expansion phase.

All decision rules are applied at the end of every year, and provide alternatives to suit risk-averse, risk-neutral, and risk-seeking decision-making profiles. They do not, however, represent all possible rules that exist for this design problem exhaustively. These are subject to the system expert elicitation process, and may vary from one application to another. These are used to demonstrate the catalog process and the ensuing analysis once feasible flexibility strategies and decision rules are elicited. Table 2 summarizes the flexible decision rules and design variables – also referred as factor – elicited in this application.

Table 2 Summary of flexible decision rules (DR) and design variables (DV) investigated in this study.

DV and DR	Factor Description	Levels
$\mathbf{a_{1\text{-}4}}$	Expansion allowed in years 1-4	Yes - No
$\mathbf{a_{9\text{-}12}}$	Expansion allowed in years 9-12	Yes - No
$\mathbf{a_{17\text{-}20}}$	Expansion allowed in years 17-20	Yes - No
dr	Expansion decision rule (years)	2 – 4
$\mathbf{f_t}$	Number of floors expanded by	1 – 3
$\mathbf{f_0}$	Number of initial floors	2 – 9

Many combinations of decision rules and design variables exist to enable and manage the flexibility, each leading to a different operating plan. It is not clear what operating plan gives better lifecycle improvement compared to a fixed baseline design for each representative scenario. One operating plan may be well suited for a particular demand scenario, but not necessarily for another. It is best to tailor each operating plan for each scenario. All combinations lead to $2^3 \times 3^2 \times 8 = 576$ possible operating plans. A level refers to the value a decision rule and/or design variable can take. The performance model is modified to enable analysis of the flexible decision rules and design variables, and to construct the design catalog in step 4.

4.1.4 Step 4: Construct the Design Catalog

In this application, the fractional factorial DOE technique called adaptive One-Factor-At-a-Time (aOFAT) [Frey and Wang, 2006] is used to explore the design space. The approach starts from a baseline configuration, and measures the response using the quantitative model. One of the factor levels is toggled to another level, and another measurement is made. If the objective function (i.e. NPV) is improved, the change is kept, and the analysis moves on to another factor and/or level. If there is no improvement, the change is discarded, and another design point is explored. The algorithm goes in sequence until all factors levels are explored once.

aOFAT reduces the number of search iterations tremendously, while still reaching a good solution. In a design space with n factors with 2-levels each, aOFAT reduces the number of experiments from 2^n to $n + 1$, while still reaching on average about 83% of the optimal response [Frey and Wang, 2006]. For n factors with m levels, the number of possible combinations is m^n, each factor being explored $m - 1$ times, and therefore $n(m - 1) + 1$ combinations are explored. Instead of facing a design space growing exponentially in n and m, designers need only to explore a number of combinations growing as a multiplicative function of n and m. This reduces the computational overhead significantly. While no study exists to guarantee the global optimality of the solutions, using aOFAT helps consider a wider and more representative range of solutions that can improve the baseline response – since by definition aOFAT progresses through the design space based on response improvement, unless the baseline response is already the best combination – while reducing computational overhead. The process for representative scenario 1 in Fig. 3 is summarized in Table 3.

Table 3 Description and output of each iteration in the aOFAT sequence for demand scenario 1.

Iteration	DV/DR changed:	DV/DR Level changed to:	NPV Output (million)	Best NPV output so far? (million)	Keep change?
1	-	-	$21.7	-	-
2	$\mathbf{f_t}$	2	$21.1	$21.7	No
3	$\mathbf{f_t}$	1	$21.0	$21.7	No
4	$\mathbf{f_0}$	2	$7.6	$21.7	No
5	$\mathbf{f_0}$	3	$12.9	$21.7	No
6	$\mathbf{f_0}$	4	$14.0	$21.7	No
7	$\mathbf{f_0}$	5	$19.1	$21.7	No
8	$\mathbf{f_0}$	7	$19.7	$21.7	No
9	$\mathbf{f_0}$	8	$22.6	$21.7	Yes
10	$\mathbf{f_0}$	9	$20.6	$22.6	No
11	$\mathbf{a_{9\text{-}12}}$	Yes	$22.6	$22.6	No
12	**dr**	2	$22.6	$22.6	No
13	**dr**	4	$22.6	$22.6	No
14	$\mathbf{a_{17\text{-}20}}$	Yes	$22.6	$22.6	No
15	$\mathbf{a_{1\text{-}4}}$	Yes	$22.6	$22.6	No

The initial design and exploration sequence are selected randomly. The baseline operating plan corresponds to vector $[a_{1\text{-}4}, a_{9\text{-}12}, a_{17\text{-}20}, dr, f_t, f_0]$ = [No, No, No, 3, 3, 6]. This design produces NPV = $21.7 million using the deterministic model in step 1. Decision rule factor f_t is changed from value $f_t = 3$ to $f_t = 2$, leading to NPV = $21.1 million. Since the response is not improved, the decision rule is set back to its original value, and then the response using $f_t = 1$ is measured. Since NPV = $21.0 million is also not an improvement compared to the baseline response, the change is also discarded. The analysis moves on to other design variables and decision rules, until all factor levels are explored once. The main change occurs when $f_0 = 8$ floors, where NPV = $22.6 million. The high capacity design captures the most value out of the high demand growth scenario.

Table 4 Design catalog I generated using aOFAT.

DVs and DRs	Op. Plan 1	Op. Plan 2	Op. Plan 3	Op. Plan 4	Op. Plan 5
$a_{1\text{-}4}$	No	Yes	Yes	Yes	No
$a_{9\text{-}12}$	No	Yes	Yes	Yes	Yes
$a_{17\text{-}20}$	No	No	No	No	Yes
dr	3	2	2	2	4
f_t	3	2	2	1	1
f_0	8	6	4	4	4

The operating plan for scenario 1 is captured by design vector [$a_{1\text{-}4}$, $a_{9\text{-}12}$, $a_{17\text{-}20}$, dr, f_t, f_0] = [No, No, No, 3, 3, 8]. This operating plan states that if demand grows very fast in early years, capacity expansion should not be allowed because it is more profitable to have as many floors installed initially as possible. NPV is insensitive to choices in flexible decision rules, because most of the capacity is already installed. A similar approach is used to generate a flexible operating plan for each of the five representative scenarios, each offering slower demand growth in the first few years. This leads to the design catalog summarized in Table 4. To better visualize an operating plan, Fig. 4 shows the typical capacity deployment occurring under operating plan 4. Such plan will be applied in phase 5 of the process whenever a given scenario is associated to representative scenario 4. It is associated to design vector [$a_{1\text{-}4}$, $a_{9\text{-}12}$, $a_{17\text{-}20}$, dr, f_t, f_0] = [Yes, yes, No, 1, 2, 4].

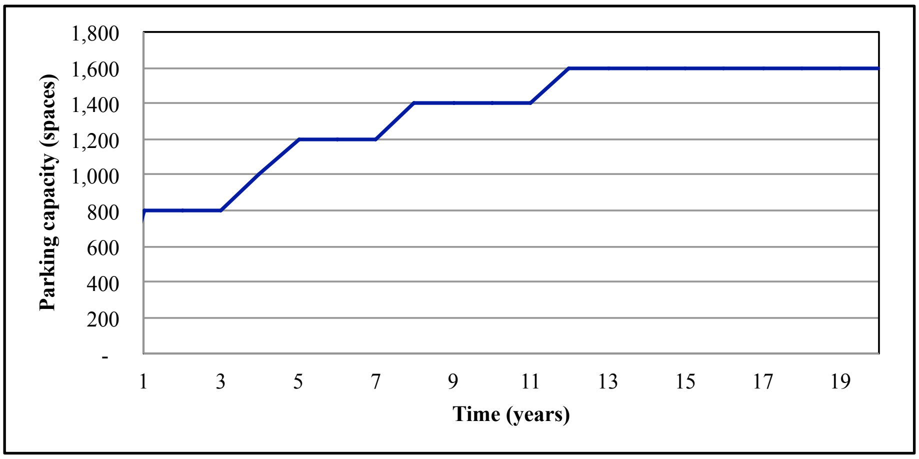

Fig. 4. Capacity deployment for operating plan 4.

4.1.5 Step 5: Evaluate the Lifecycle Performance of the Catalog

This step takes the catalog of operating plans constructed in step 4 and simulates the ability of the system operator to choose between different flexible operating plans, based on Monte Carlo simulations. Equation 7 is modified to account for the stochastic nature of demand, and to perform out-of-sample testing:

$$D_{t+1}{}^{S} = g_t(1 + D_t) \qquad (8)$$

In Equation 8, D_t is calculated as before, although now D_1, additional demand by year 10, and additional demand by final year are random variables sampled from a uniform distribution with values ± 50% off the initial projection. Inter-annual demand growth g_t is modeled using Geometric Brownian Motion (GBM): $g_t = g_p dt + \sigma dW_t \sqrt{dt}$, where $g_p = D_t/D_{t-1} - 1$ is the projected inter-annual demand growth obtained using the stochastic version of the demand model, dt = 1 year time increment, σ = 15% is the assumed volatility of demand. Variable dW_t is the Wiener process, in this case sampled from a uniform distribution U ~(-1, 1) instead of a normal distribution for faster computations.

Using the stochastic demand model, the rigid design ($f_0^* = 6$) gives rise to an average NPV (or expected NPV, ENPV) $ENPV_{inflex.}$ = \$8.0 million under 2,000 demand scenarios. This design is also the stochastic optimal design (i.e. maximizing ENPV), and therefore the baseline rigid design for this study.

Fig. 5 shows a sample scenario alongside the original deterministic demand projection. In this sample, since growth is about 35% between years 1-5 (from 690 to 931), the scenario is associated to representative scenario 5, and operating plan 5 is applied. Fig. 6 shows the lifecycle effect of the operating plan on an Excel® implementation of the DCF model, leading to NPV = \$17.4 million. Even though operating plan 5 is conservative in the first years, it enables a series of aggressive expansions (fourth row from top) after year 5, when demand starts picking up. The same process is applied to all 2,000 demand scenario samples in the simulation. Each scenario is assigned to one of the five operating plans. Design variables and decision rules lead to a different expansion path for each scenario, leading each time to a different NPV.

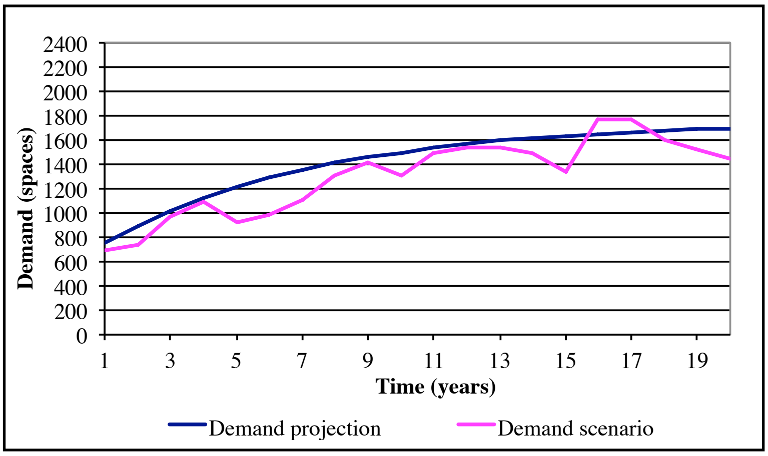

Fig. 5. Example simulated demand scenario assigned to operating plan 5.

Fig. 7 shows the cumulative distribution functions – also referred as target curves – for the stochastic optimal inflexible baseline design with six floors, and using the design catalog approach. The target curve resulting from the catalog approach dominates the one from the inflexible 6-floor design. The resulting distribution of operating plan assignments is shown in Fig. 8. Table 5 summarizes the results according to different evaluation criteria: ENPV, 5^{th} percentile (P5) or value at risk, P95 or value at gain, standard deviation, expected initial investment, and expected value of flexibility. The goal of reporting different evaluation metrics is to accommodate different risk profiles in decision-making. For example, a risk-averse decision-maker may prefer designs that maximize the worst possible outcome (measured via P5), minimize volatility and risk as measured by the standard deviation, and/or minimize the expected initial investment. A risk-neutral decision-maker may favor a design maximizing ENPV – since s/he is indifferent between maximizing upsides and minimizing the impact of downside scenarios. A risk-seeking decision-maker may prefer maximizing the best possible outcome and gain (measured via P95). Table 5 does not include all possible performance metrics, but provides guidance to suit a range of decision-making profiles.

Year	0	1	2	3	4	5	6	7	8	9	10
Realised demand		690	733	964	1,088	931	986	1,104	1,310	1,420	1,305
Capacity	-	800	800	800	800	800	800	1,000	1,200	1,400	1,600
Expansion?							expand	expand	expand	expand	
Expansion (using expansion operating plan)?											
Build extra capacity	0	0	0	0	0	0	200	200	200	200	0
Revenue	$0	$6,900,000	$7,333,222	$8,000,000	$8,000,000	$8,000,000	$8,000,000	$10,000,000	$12,000,000	$14,000,000	$13,050,245
Operating costs	$0	$1,600,000	$1,600,000	$1,600,000	$1,600,000	$1,600,000	$1,600,000	$2,000,000	$2,400,000	$2,800,000	$3,200,000
Land leasing costs	$3,600,000	$3,600,000	$3,600,000	$3,600,000	$3,600,000	$3,600,000	$3,600,000	$3,600,000	$3,600,000	$3,600,000	$3,600,000
Expansion cost			$0	$0	$0	$0	$4,259,200	$4,685,120	$5,153,632	$5,668,995	$0
Cashflow	$0	$1,700,000	$2,133,222	$2,800,000	$2,800,000	$2,800,000	-$1,459,200	-$285,120	$846,368	$1,931,005	$6,250,245
DCF		$1,517,857	$1,700,592	$1,992,985	$1,779,451	$1,588,795	-$739,276	-$128,974	$341,834	$696,340	$2,012,412
Present value of cashflow	$26,339,961										
Capacity cost for up to two levels	$6,400,000										
Capacity costs for levels above 2	$7,392,000										
Net present value	$8,947,961										
Total initial cost	$17,392,000										

Fig. 6. DCF analysis resulting from applying operating plan 5 to the simulated demand scenario from Fig. 5. Only years 1-10 are shown out of a 20 years lifecycle.

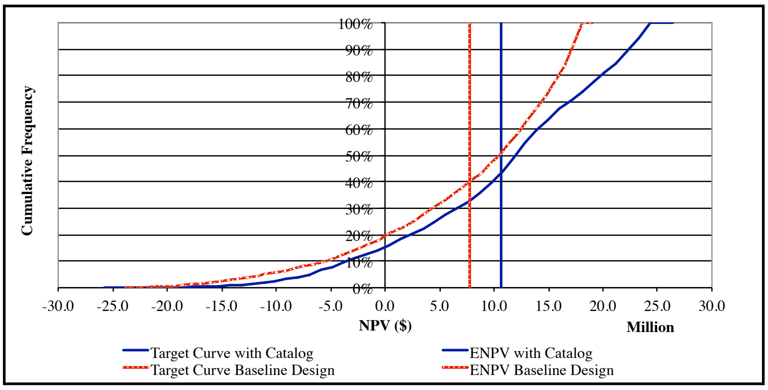

Fig. 7. Cumulative distribution functions – or target curves – for the inflexible 6-floor baseline design, and using the design catalog generated using aOFAT.

The results in Table 5 show that the design catalog approach produces better results on almost all criteria. The expected value increase provided by flexibility and recognized via the design catalog approach is calculated as $E[V_{Catalog}] = ENPV_{Catalog} - ENPV_{Inflexible}$ = \$2.9 million. This is a 37% improvement compared to the stochastic optimal inflexible baseline design with six floors. The main advantage of the inflexible design is to provide a tighter distribution of outcomes, shown by a slightly lower standard deviation.

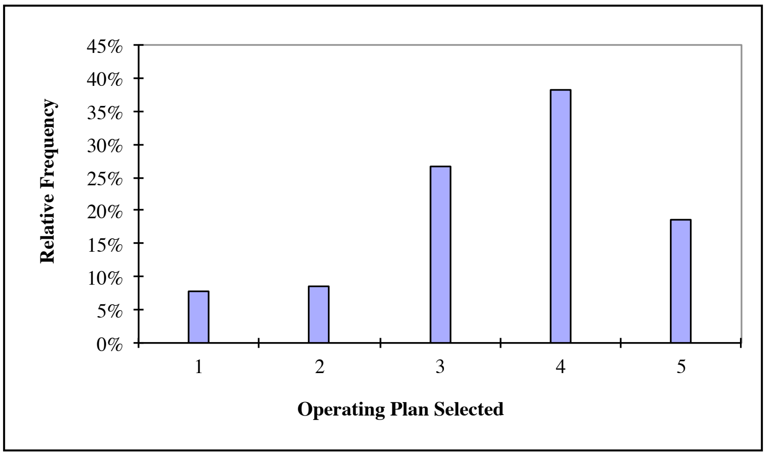

Fig. 8. Relative frequency of each operating plan to each demand scenario in using design catalog I constructed using aOFAT.

Table 5 Multi-criteria evaluation of the design alternatives for each evaluation technique, using aOFAT to construct the catalog of operating plans in case study I. All values are in $ (million).

	Deterministic	Inflexible	Catalog	Preferred?
ENPV	10.6	7.8	10.7	Catalog
P5 (Value At Risk)	N/A	-11.2	-6.9	Catalog
P95 (Value At Gain)	N/A	17.6	23.4	Catalog
Standard Deviation	N/A	9.1	9.5	Inflexible
E[Initial Investment]	22.7	22.7	16.1	Catalog
E[Value of Catalog]	-	-	2.9	

4.2 Sensitivity Studies

This section evaluates critically the process in steps 2, 4, and 5 under different sets of assumptions. In step 1, a sensitivity analysis can be done on the main economic and engineering parameters, but it is of limited interest given that the focus is on understanding how the construction and evaluation change under different assumptions. In step 3, other sources of flexibility could be analyzed, but this does not add to the scope of the paper, which aims at introducing the catalog process, and demonstrating how to apply it. Abandonment, staged capacity deployment, and switching real options have been analyzed in similar applications of the process in mining and real estate problems [Cardin, de Neufville, Geltner and Deng, 2013, Cardin, de Neufville and Kazakidis, 2008] showing that the process can handle the analysis of other flexible systems design concepts, and for different infrastructure systems.

4.2.1 Step 2: Finding Representative Uncertainty Scenarios

The scenario planning technique may lead to different numbers and forms of representative scenarios, depending on users, context, and organization. Choosing such scenarios is critical as it influences the design catalog, and ultimately the results. Additional analyses are conducted using k = 2, 3, and 4 representative scenarios out of n = 5 available scenarios. The combinations shown in Table 6 were randomly selected, since there are $C(n, k)$ possible combinations for each set, and it is impossible to show here all possible results. The same mid-values from Table 1 were used to assign a demand scenario to an operating plan. Results show that using fewer operating plans still improves value without the need to perform an exhaustive flexibility analysis. Here, a catalog consisting of four operating plans (OP) – namely OP 2-5 – provides the best overall results.

Table 6 Results obtained using different representative scenarios and operating plans. OP: operating plan; SD: standard deviation; E[Invest.] = E[Initial Investment]; E[Flex.] = E[Value of Flexibility].

	Inflex.	OP 1-5	OP 2-5	OP 1, 3, 5	OP 2, 4	Preferred?
ENPV	7.8	10.7	11.0	9.7	10.6	OP 2-5
P5	-11.2	-6.9	-4.0	-9.4	-7.4	OP 2-5
P95	17.6	23.4	23.0	23.3	23.3	OP 1-5
SD	9.1	9.5	8.2	10.3	9.6	OP 2-5
E[Inv.]	22.7	16.1	15.4	16.8	17.6	OP 2-5
E[Flex.]	-	2.9	3.2	1.9	2.8	OP 2-5

4.2.2 Step 4: Construct the Design Catalog

The results above are obtained using aOFAT. This is not the only suitable mechanism to construct the catalog. Two additional catalogs are constructed using a) an evolutionary optimization algorithm, and b) using full factorial analysis to explore the design space for each representative scenario. Table 7 shows design catalog II using an evolutionary optimization algorithm in Excel® for Mac 2011 version 14.1.4. This one differs from the one obtained with aOFAT, but is similar to the one obtained using full exhaustive search described next.

Table 7 Design catalog II generated using Excel®'s evolutionary optimization algorithm.

DVs and DRs	Op. Plan 1	Op. Plan 2	Op. Plan 3	Op. Plan 4	Op. Plan 5
$\mathbf{a_{1\text{-}4}}$	Yes	Yes	Yes	Yes	Yes
$\mathbf{a_{9\text{-}12}}$	No	Yes	Yes	Yes	Yes
$\mathbf{a_{17\text{-}20}}$	Yes	Yes	No	No	Yes
dr	2	2	2	2	2
$\mathbf{f_t}$	3	3	2	1	1
$\mathbf{f_0}$	6	5	4	4	4

Table 8 shows design catalog III obtained by evaluating all 576 possible combinations of design variables and decision rules under each representative scenario. The operating plans are all different from catalogs I and II, except for operating plan 4. Only operating plan 1 under aOFAT is significantly different from catalogs II and III, starting with 8 floors as opposed to 6 when using exhaustive search and optimization. This shows that aOFAT can offer myopic results in some cases, due to the local nature of the search algorithm.

Table 9 compares the results obtained with the different catalogs under different performance metrics taken individually (i.e. not as a multi-criteria function). They show a) that the catalog approach generates better value compared to the inflexible baseline design solution no matter what the search process is, and b) expectedly the full factorial search leads to the best results for most criteria.

Table 8 Design catalog III generated using full factorial analysis in Excel®.

DVs and DRs	Op. Plan 1	Op. Plan 2	Op. Plan 3	Op. Plan 4	Op. Plan 5
a_{1-4}	Yes	Yes	Yes	Yes	Yes
a_{9-12}	No	No	No	Yes	No
a_{17-20}	No	No	No	No	No
dr	2	2	2	2	2
f_t	3	3	2	1	1
f_0	6	5	4	4	4

Table 9 Multi-criteria comparison of the inflexible design with the design catalogs constructed using aOFAT, evolutionary optimization, and full factorial analysis. All values in $ million.

	Inflex.	Cat. I aOFAT	Cat. II Optim.	Cat. III FF	Preferred?
ENPV	7.8	10.7	11.4	11.8	Catalog III
P5	-11.2	-6.9	-4.3	-4.0	Catalog III
P95	17.6	23.4	23.2	23.2	Catalog I
SD	9.1	9.5	8.6	8.6	Catalogs II/III
E[Inv.]	22.7	16.1	15.0	15.0	Catalogs II/III
E[Flex.]	-	2.9	3.6	4.0	Catalog III

As expected, design catalog III offers the best results under most economic performance metrics. Full factorial analysis, however, requires evaluating all 576 combinations of design variables and decision rules, which can be expensive on applications with a model running slowly. It takes < 1 second to run aOFAT and a full factorial analysis using Data Tables in Excel® for Mac 2011 on a standard MacBook Pro laptop running Mac OSX 10.8, with 3 GHz Intel Core i7, and 8 GB 1,600 MHz DDR3 RAM. The optimization algorithm requires evaluation of 5388, 4049, 3289, 3556, and 3189 sub-problems per representative scenario, and on average ~1 minute computational runtime. The sub-problems emerge from the mutation, crossover, and natural selection steps inherent to the evolutionary algorithm evaluating different combinations in a systematic way. In contrast, constructing design catalog I using aOFAT requires evaluating only 15 different combinations per representative scenario, which is less than 3% of the full design space, while reaching nearly 91% of the ENPV response of design catalog III ($10.7 million/$11.8 million). The evolutionary algorithm achieves a better response than aOFAT while also not exploring the full design space. It requires significantly more runtime, due to the higher complexity of the algorithm. The results show that constructing a catalog using aOFAT provides good results while significantly reducing the number of configurations to analyze.

4.2.3 Step 5: Evaluate the Lifecycle Performance of the Catalog

A fair comparison of the results obtained here with those generated using existing techniques in the literature is challenging. This is because a design catalog accounts for managerial flexibility in two ways. First, it recognizes managers' ability to change operating plan as needed. Second, it recognizes the flexibility to adapt within a given operating plan. Most of existing research only provides ways to identify the stochastic optimal flexible design alternative. For instance, Yang [2009] and Lin et al. [2013] found the flexible design solution that optimizes ENPV, or other performance metrics like P5, P95, etc. Although in both studies the solution is optimal, it represents only one operating plan, which is applied consistently throughout the system lifecycle.

The solutions identified here are nonetheless compared along two dimensions. The first comparison is to determine whether the catalog approach improves the expected lifecycle performance of the system as compared to the best inflexible benchmark design – also addressing the secondary research question. This is a fair comparison, because the stated goal of the process is to improve system performance as compared to the benchmark – and not necessarily to guarantee stochastic optimality. Indeed, Table 5-6 and Table 9-10 show performance improvements when comparing the inflexible benchmark design to the different catalogs, and along most evaluation metrics.

The second comparison is to evaluate the performance of the catalog relative to the stochastic solution. Such analysis requires evaluating all 576 possible design solutions under 2,000 out-of-sample demand scenarios. The stochastic solution is $[a_{1\text{-}4}, a_{9\text{-}12}, a_{17\text{-}20}, dr, f_t, f_0]^*$ = [Yes, No, No, 2, 1, 5] with $ENPV_{flex.}$ = \$12.5 million. Results are summarized in Table 10.

Table 10 Multi-criteria evaluation using aOFAT to construct the design catalog, and stochastic optimization (SO). All values are in $ (million).

	Deterministic	Inflexible	Catalog	SO	Preferred?
ENPV	10.6	7.8	10.7	12.5	SO
P5	N/A	-11.2	-6.9	-4.7	SO
P95	N/A	17.6	23.4	26.3	SO
SD	N/A	9.1	9.5	9.5	Same
E[Inv.]	22.7	22.7	16.1	18.1	Catalog
E[Flex.]	-	-	2.9	4.7	SO

While the global solution provides better expected performance, it does not recognize managers' ability to change between different operating plans during the project lifetime. Also, such analysis requires significant computational runtime (i.e. ~26 seconds on average per evaluation under 2,000 scenarios x 576 evaluations ≈ 4.1 hours) using Matlab R2010b. In contrast, constructing the design catalog requires evaluating 75 feasible design solutions (15 combinations per representative scenario x 5 scenarios) taking on average < 1 second each once automated. Running a Monte Carlo simulation with 2,000 out-of-sample demand scenarios, and assigning each scenario to one of the five operating plans takes on average ~4 seconds. The entire analysis takes < 80 seconds on average. This is nearly 183 times faster than the stochastic optimization analysis described above.

The stochastic optimization is tractable in this application for demonstration purposes, and to understand the properties of the catalog process. Such optimization will most likely not be tractable in applications where a high-fidelity model is used, as often done in the mining and/or oil and gas industries, or if a more complex system with more design variables, uncertainty sources, and decision rules is analyzed. In these industries, models take routinely several hours if not several days to find a single optimal operating plan to one deterministic scenario of main uncertainty drivers [Cardin, de Neufville and Kazakidis, 2008, Lin, de Neufville, de Weck and Yue, 2013]. For instance, oil companies typically use separate high-fidelity models for sub-reservoir capacity, fluid flow physics, and economic evaluation, requiring days to optimize one design configuration. Mining companies use high-fidelity resource allocation models also taking several days to construct a single optimal plan for exploiting the mine. While it is true that decision-makers may well afford many days of computations to support multi-million and billion dollar decisions, there are cases where the computational problem is simply too prohibitive or plainly intractable to perform, and/or situations requiring faster progress to the more detailed phase of the design process. The procedure proposed here is adding to the designer's toolkit, depending on the situation they face, and the time/resources available for the analysis.

In cases where a high-fidelity model is used, the design catalog approach combined with aOFAT can be particularly useful. It only requires analyzing a few design configurations, representing sizeable savings in terms of computational time and analytical resources. Out-of-sample evaluation using the process described in step 5 can then be done inexpensively to determine how the proposed catalog fares as compared to other solutions, without the need to explore the entire design space.

5 Discussion

The analysis above answers the main research question, since application of the proposed five-step process is shown successfully to analyze flexibility in the design of an infrastructure system operating under uncertainty. The second research question is addressed because the process is shown to improve lifecycle performance as compared to the outcome of standard design and evaluation methods. The process also has valuable properties as compared to existing techniques based on stochastic optimization and DOE, and for practical uses.

First, the catalog process improves the expected lifecycle performance compared to a stochastically optimal inflexible baseline design obtained via standard evaluation practice. It recognizes in the evaluation process that operators will adapt intelligently to different scenarios during operations. Such flexibility has value that can be considered explicitly in early evaluation and design phases, and embedded physically in the design. Otherwise, design alternatives offering less performance may be selected and implemented.

Steps 2-3 of the process help stimulate creativity and insights on how to recognize and generate additional value from flexibility. Steps 4-5 help measure such expected performance improvement, building upon the performance model developed in step 1. Value improvement stems from the ability to reduce downside losses when demand is not growing fast enough, by reducing initial investment, and by avoiding unnecessary capacity deployment when it does not grow rapidly enough. It also stems from the ability to change operating plan as exogenous conditions change. This approach positions the system to capture more value from upside opportunities, and reduce the impact from downside events. It is also suitable for evaluation based on different performance metrics (e.g. P5, P95, etc.)

Second, the proposed process provides a systematic approach to analyze uncertainty and flexibility in early design decision-making phases that a) does not rely on traditional ROA techniques – and therefore is not limited by their implicit assumptions – and b) relies on standard deterministic optimization techniques while still accounting for uncertainty via Monte Carlo simulation. The approach reduces computational burden without the need to rely on more advanced stochastic optimization techniques, while still reaching a good solution.

Third, the approach provides a solution that is easy to manage, implement, and builds upon what is currently done in practice. The following illustrates how the catalog technique could be used to manage the example system. First, demand is projected at $t = 0$ for years 1-5, and the initial development and management is based on the corresponding operating plan in Table 4. If, for example, projection is assigned to representative scenario 4 ($0.38 < \beta < 0.68$), the initial design should have four floors to follow the recommendation of operating plan 4, and managers should account for a one-floor expansion every time demand exceeds capacity for two consecutive years in periods 1-4 and 9-12. Revisions to the management rules can then be made every five years, as needed, to account for possible changes in operating plans over the project lifetime.

The proposed process has several properties that make it useful for practical applications. It is generic and systematic, so designers and decision-makers can apply it to analyze different system problems. In phase 1, analysts can choose the modeling technique to measure the system performance based on the suggestions provided, or the approach already in use at the organization. In phase 2, several techniques are suggested to identify representative scenarios so that users can identify those that are most significant to the system at hand. Such choice may also rely solely on the analyst's expertise and experience with the system, without the need to use more formal methods. Phase 3 relies specifically on such expertise, and on the analyst's creativity with the system. It provides the necessary structure to "think out of the box", and consider other solutions that may not normally be considered through standard and project evaluation processes by explicit consideration of flexibility. In phase 4, several quantitative techniques can be used to explore the design space. The main idea is to construct the catalog so that the system provides a good response in adaptation to different uncertainty realizations. This can even be done manually, if analysts know of a better outcome or solution, without the need for a systematic search. The creative ideas from phase 3 are really put to test via quantitative evaluation of the design catalog in phase 5. This is important to discriminate between different possible solutions, and to identify those that are more likely to enhance performance and value.

5.1 Limitations and Results Validity

This section discusses the limitations of the proposed process, and the validity of the results. In phase 1, the validity of the valuation results to assist in the decision-making process relies heavily on the ability of the model to capture essential performance tradeoffs. Validation of the numerical results, however, is challenging due to the typically long lifecycle of complex engineering systems. To this end, the DCF modeling approach captures best practices in finance and large-scale engineering firms to assess the future economic performance of investment projects. In phase 2, results can be affected greatly by the choice of representative scenarios and uncertainty drivers. Designers must use caution in their analysis of uncertainty, and be modest in the number of drivers/scenarios they can consider and their ability to characterize uncertainty. Choosing different scenarios and categorization parameters may lead to significantly different results and recommendations. Thus, this initial study sets a research agenda to improve the method of finding representative scenarios. The work on scenario planning, probability elicitation techniques, and case-based reasoning provide good directions for further developments [Morgan and Henrion, 1990, Helmer-Hirschberg, 1967, Schoemaker, 1995, Reich and Kapeliuk, 2004]. In step 3, only capacity expansion was analyzed for demonstration purposes, but more flexibility sources can be studied. Although out of scope for the present paper, validating the process on the analysis of a more complex system, accounting for more design variables and decision rules, is needed. A similar approach was used to support a consulting case in mining operations [Cardin, de Neufville and Kazakidis, 2008]. The focus of the study was on the results, however, as opposed to the methodology, which is the focus of this paper. Such application in mining provides further support to the view that the process is applicable in the real world, although an example study in parking infrastructure was used here to illustrate the overall approach. Thus, another opportunity for future extension of the work is to thoroughly study the application process of the proposed method in practice, and share the experience and insights gained by the system managers and analysts. In step 4, the results obtained using aOFAT were compared to those obtained using an evolutionary algorithm, and full factorial analysis. While aOFAT found a good solution, it did not find the global optimum for each representative scenario, which is an important limitation. Additional work is needed to compare other optimization and space sampling techniques to construct the catalog. Also, it is unclear how the operating plans can be constructed for iso-performance analysis, or when the objective is not necessarily to optimize performance under each representative scenario. In step 5, comparison with stochastic optimization showed that the catalog approach does not generate as much value as the global optimal configuration. While this is expected, the loss in value is explained by the fact that simulated demand scenarios are categorized based on a quick and efficient criterion (i.e. 5-year growth) that may not be the best, and may lead to sub-optimal classification if demand evolves differently over the following years. Also, while finding the global optimum was possible in this study, it may not be possible when optimizing the system using a high-fidelity model. More studies should apply the technique in a context where it may not be possible to find the global optimum, as a way to demonstrate general applicability in industry.

Here, a 37% improvement in expected lifecycle performance was observed compared to the best inflexible benchmark design, while exploring less than 3% of the design space for each representative scenario. The design catalog generated using aOFAT reached nearly 91% of the ENPV obtained by the catalog constructed using full factorial analysis, and 88% compared to the preferred stochastic solution for the flexible design. The design catalog approach reached the preferred solution 183 times faster than stochastic optimization in terms of computational runtime. The fact that the catalog approach generated improvements with so little computations shows that it has good potential for designers having limited time and analytical resources, or not having the resources to conduct more advanced real options and/or stochastic optimization analyses.

The cause and effect relationships reported here depend on the modeling assumptions and model validity. The results reported here are deemed internally valid and reliable because the same set of assumptions was used to analyze each scenario, compare each design alternative, and each design catalog. They are useful to rank order the design alternatives relative to one another in terms of expected performance (i.e. inflexible vs. flexible systems). It is difficult, however, to fully validate the valuation results, because of the typically long lifecycle of such system. Important features of the process are thus to enable recognition and creation of value-adding flexibility, to enable relative rank ordering of different solutions, and to do so in a computationally efficient manner. The process may be generalizable to other engineering systems, since a similar version was applied successfully to analyze other systems in the real estate and mining industries [Cardin, de Neufville, Geltner and Deng, 2013, Cardin, de Neufville and Kazakidis, 2008]. Such external validity must be, however, further validated with more industry applications and studies in practice.

6 Conclusion

This paper presents a novel process to improve current systems design and evaluation practice that often relies on simplifying assumptions regarding the main uncertainty drivers affecting lifecycle performance in engineering systems. The proposed process bundles a set of representative uncertainty scenarios obtained using probability elicitation and scenario planning techniques within a design catalog consisting of key operating plans. Each operating plan provides an appropriate flexible response to a representative uncertainty scenario. This enables recognizing upfront intelligent managerial decisions in design and management, stemming from the flexibility embedded early in the system design, without relying on more advanced real options and stochastic programming techniques. It alleviates computational challenges typically related to such extended design and evaluation analysis.

The catalog approach was applied to the analysis of an example infrastructure system, a particular class of engineering system. It shows 37% improvements in expected lifecycle performance compared to the baseline design developed from standard design and evaluation practice. The analysis explores less than 3% of the design space, representing significant economies in terms of computational runtime and analytical resources, while reaching 88-91% of the response obtained with full factorial and stochastic optimization methods. Even though the process is promising, more work is needed to fully validate its use across different systems and industries.

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References

1. ESD, "Engineering systems division strategic report," Massachusetts Institute of Technology, Cambridge, MA, United States 2011.

2. INCOSE, Incose systems engineering handbook: A guide for system life cycle processes and activities, 4th edition, Wiley, 2015.

3. R. de Neufville, and S. Scholtes, Flexibility in engineering design, MIT Press, Cambridge, MA, United States, 2011.

4. L. Trigeorgis, Real options, MIT Press, Cambridge, MA, United States, 1996.

5. M.-A. Cardin, Enabling flexibility in engineering systems: A taxonomy of procedures and a design framework, Journal of Mechanical Design 136 (2014), 011005-011005.

6. M.R. Silver, and O.L. de Weck, Time-expanded decision networks: A framework for designing evolvable complex systems, Systems Engineering 10 (2007), 167-186.

7. R. Nilchiani, and D.E. Hastings, Measuring the value of flexibility in space systems: A six-element framework, Systems Engineering 10 (2007), 26-44.

8. O.L. de Weck, R. de Neufville, and M. Chaize, Staged deployment of communications satellite constellations in low earth orbit, Journal of Aerospace Computing, Information, and Communication 1 (2004), 119-136.

9. T. Mikaelian, D.J. Nightingale, D.H. Rhodes, and D.E. Hastings, Real options in enterprise architecture: A holistic mapping of mechanisms and types for uncertainty management, IEEE Transactions on Engineering Management 54 (2011), 457-470.

10. S.X. Zhang, and V. Babovic, An evolutionary real options framework for the design and management of projects and systems with complex real options and exercising conditions, Decision Support Systems 51 (2011), 119-129.

11. T. Tomiyama, P. Gu, Y. Jin, D. Lutters, C. Kind, and F. Kimura, Design methodologies: Industrial and educational applications, CIRP Annals – Manufacturing Technology 58 (2009), 543-565.

12. O.L. de Weck, and C. Eckert, "A classification of uncertainty for early product and system design," *ESD Working Paper Series*, Massachusetts Institute of Technology, Cambridge, MA, United States, 2007.

13. M.-A. Cardin, G.L. Kolfschoten, D.D. Frey, R. Neufville, O.L. Weck, and D.M. Geltner, Empirical evaluation of procedures to generate flexibility in engineering systems and improve lifecycle performance, Research in Engineering Design 24 (2013), 277-295.

14. T. Mikaelian, D.H. Rhodes, D.J. Nightingale, and D.E. Hastings, A logical approach to real options identification with application to uav systems, IEEE Transactions on Systems, Man, and Cybernetics: Part A 42 (2012), 32-47.

15. H.T.J. Smit, Acquisition strategies as option games, Journal of Applied Corporate Finance 14 (2001), 79-89.

16. M.-A. Cardin, Y. Jiang, H.K.H. Yue, and H. Fu, Training design and management of flexible engineering systems: An empirical study using simulation games, Systems, Man, and Cybernetics: Systems, IEEE Transactions on 45 (2015), 1268-1280.

17. F. Black, and M. Scholes, The pricing of options and corporate liabilities, Journal of Political Economy 81 (1973), 637-654.

18. J.C. Cox, S.A. Ross, and M. Rubinstein, Options pricing: A simplified approach, Journal of Financial Economics 7 (1979), 229-263.

19. P. Kall, and S.W. Wallace, Stochastic programming, John Wiley and Sons, Chichester, 1994.

20. D.A. Romero, C.H. Amon, and S. Finger, Multiresponse metamodeling in simulation-based design applications, Journal of Mechanical Design 134 (2012), 091001-091001.

21. T. Wang, "Real options in projects and systems design – identification of options and solutions for path dependency," Massachusetts Institute of Technology, Cambridge, MA, United States, 2005.

22. J. Lin, R. de Neufville, O.L. de Weck, and H.K.H. Yue, Enhancing the value of oilfield developments with flexible subsea tiebacks, Journal of Petroleum Science and Engineering 102 (2013), 73-83.

23. M. Ranjbar Bourani, M.-A. Cardin, W.S. Chong, R. Atapattu, and K.S. Foo, "An integrated screening framework to analyze flexibility in engineering systems design," *International Conference on Engineering Design*, Seoul, Korea, 2013.

24. Y. Yang, "A screening model to explore planning decisions in automotive manufacturing systems under demand uncertainty," Massachusetts Institute of Technology, Cambridge, MA, United States, 2009.

25. A.M. Ross, "Managing unarticulated value: Changeability in multi-attribute tradespace exploration," Massachusetts Institute of Technology, Cambridge, MA, United States, 2006.

26. M.G. Morgan, and M. Henrion, Uncertainty: A guide to dealing with uncertainty in quantitative risk and policy analysis, Cambridge University Press, United Kingdom, 1990.

27. O. Helmer-Hirschberg, "Analysis of the future: The delphi method," RAND Corporation, 1967.

28. P.J.H. Schoemaker, Scenario planning: A tool for strategic thinking, Sloan Management Review 36 (1995), 25-40.

29. Y. Reich, and A. Kapeliuk, Case-based reasoning with subjective influence knowledge, Applied Artificial Intelligence 18 (2004), 735-760.

30. J. Hu, and M.-A. Cardin, Generating flexibility in the design of engineering systems to enable better sustainability and lifecycle performance, Research in Engineering Design 26 (2015), 121-143.

31. G. Box, W. Hunter, and J. Hunter, Statistics for experimenters, John Wiley and Sons, 1978.

32. J. Holland, Adaptation in natural and artificial systems, University of Michigan Press, MI, United States, 1975.

33. S. Kirkpatrick, C.D. Gelatt, and M.P. Vecchi, Optimization by simulated annealing, Science 220 (1983), 671-680.

34. J. Kennedy, and R. Eberhard, Particle swarm optimization, IEEE International Conference on Neural Networks, 1995, pp. 1942-1945.

35. P.E. Gill, W. Murray, and M.H. Wright, Practical optimization, Academic Press, 1986.

36. R. de Neufville, S. Scholtes, and T. Wang, Valuing options by spreadsheet: Parking garage case example, ASCE Journal of Infrastructure Systems 12 (2006), 107-111.

37. D.D. Frey, and H. Wang, Adaptive one-factor-at-a-time experimentation and expected value of improvement, Technometrics 48 (2006), 418-431.

38. M.-A. Cardin, R. de Neufville, D. Geltner, and Y. Deng, "Design catalogs: A practical real options valuation tool for real estate design and development planning," *Real Options Conference*, Tokyo, Japan, 2013.

39. M.-A. Cardin, R. de Neufville, and V. Kazakidis, A process to improve expected value in mining operations, Mining Technology: IMM Transactions, Section A 117 (2008), 65-70.

7 Appendix

7.1 Modeling Data

Table 11 Master table summarizing lower (LB) and upper bound (UB) values for design variables (DV), parameters (DP), constraints (C), and objective functions (O) for the parking garage system.

Symbol	Description	[LB, UB]	Initial Value	Units	Type
c_c	Construction cost per parking space	-	16,000	[$]	DP
c_l	Annual leasing land cost	-	3,600,000	[$]	DP
c_r	Operating cost per parking space	-	2,000	[$]	DP
cc_t	Total construction cost at year t	-	$f(c_c, g_c, k_0)$	[$]	C
C_t	Total cost at year t	-	$f(cc_t, c_e, c_l, c_r, k_t)$	[$]	C
f_0	Number of initial floors at year 0	2 - 9	6	[floors]	DV
g_C	Constr. cost growth per floor above two	-	10%	[%]	DP
k_t	Total parking space capacity at year t	400 - 1,800	$f(f_0, n_0, f_t)$	[spaces]	C
n_0	Initial number of parking space/floor	-	200	[spaces]	DP
NPV	Net Present Value	None	-	[$]	O
p	Price per parking space	-	10,000	[$]	DP
R_t	Total revenues at year t	None	$f(k_t, p, D_t)$	[$]	C
r	Discount rate	-	12%	[%]	DP
T	Project duration	-	20	[years]	DP
	(Below apply to flexible design)				
a_{1-4}	Expansion allowed in years 1 to 4	Yes - No	Yes	-	DR
a_{9-12}	Expansion allowed in years 9 to 12	Yes - No	Yes	-	DR
a_{17-20}	Expansion allowed in years 17 to 20	Yes - No	Yes	-	DR
c_e	Expansion cost at time t	-	$f(c_c, f_t, g_c, k_t, n_0)$		
c_f	Cost of acquiring the flexibility	-	0	[$]	C
c_p	Percentage cost of flexibility	-	0%	[%]	DP
dr	Number of years with demand > capacity	2 - 4	2	[years]	DR
f_{max}	Maximum number of floors	-	9	[floors]	C
f_t	Number of floors expanded in year t	1 - 3	1	[floors]	DV

7.2 Procedure for generating representative scenarios

This process is inspired from scenario-planning by Schoemaker [1995]:

a) Defining the scope
    a. What is the time frame and scope of the analysis?
    b. Consider markets, geographic areas, technologies
b) Identifying major stakeholders
    a. Who will have interest in this engineering system, who will be affected, who can influence it?
    b. Examples include customers, suppliers, competitors, employees, shareholders, government
c) Identifying basic trends
    a. What political, economic, societal, technological, legal, and industry trends will affect the issue identified in step 1?
    b. Think of a discrete number of representative trends (e.g. low, medium, high economic growth; slow initial demand ramping quickly; favorable or unfavorable regulatory environments)
d) Identifying key uncertainties
    a. What events that are uncertain will significantly affect the issues of concerns?
    b. Consider the major uncertainty drivers in terms of the trends identified in the previous step
e) Constructing initial scenario themes
    a. Consider extreme worlds such as putting all positive elements into one scenario, and all negative elements into another, then combine elements in various ways to generate intermediate scenarios
f) Check for consistency and plausibility
    a. Are the trends compatible with the chosen timeframe?
    b. Do scenarios combine outcomes of uncertainties that go together?
    c. Can the major stakeholders be placed in a position they do not like and will want to change?
g) Develop learning scenarios
    a. Are there strategically relevant themes, and how can one organize possible trends and outcomes around them?
h) Identify research needs
    a. Is there a need for more research to further refine the scenarios?
i) Developing quantitative models
    a. Examine the internal consistencies of the scenarios and determine how to formalize their interaction with the system via a quantitative model
j) Evolve toward decision scenarios
    a. Do the scenarios help the organization spur further creativity and/or appreciate the up and downside events that may occur and affect the system’s lifecycle performance?

8 Acronyms

aOFAT	=	adaptive one factor at a time
C	=	constraint
DCF	=	discounted cash flow
DP	=	design parameter
DOE	=	design of experiment
DSM	=	design structure matrix
DV	=	design variable
ENPV	=	expected net present value
IRR	=	internal rate of return
LB	=	lower bound
MATE	=	multi-attribute tradespace exploration
NPV	=	net present value
O	=	objective function
OOIP	=	original oil in place
ROA	=	real options analysis
ROI	=	return on investment
SO	=	simulation-based optimization
UB	=	upper bound