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Improving the Lifecycle Performance of Engineering Projects with Flexible Strategies: Example of On-Shore LNG Production Design

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ABSTRACT

This paper presents an innovative flexibility analysis as a practical, effective procedure to improve the expected value of large-scale, capital-intensive projects when there is market uncertainty. Its novelty lies in its approach and scope. Its approach develops understanding of the drivers of the value of flexibility, so as to build acceptance among decision-makers. Its scope explicitly considers the combined effects of uncertainty, economies of scale, learning, and geographic distribution. It demonstrates how these factors combine to impact the benefits of flexibility in the early stages of design and project evaluation in the context of uncertainty. It makes this point through a specific example: the long-term deployment of liquefied natural gas (LNG) technology to supply the transportation market. It contrasts the base case fixed design (a big centralized production facility) with flexible modular designs that phase capacity additions over time and space. The proposed flexibility method compares design alternatives based on several indicators of economic lifecycle performance (Net Present Value (NPV), Initial Capex, etc.). Results indicate that flexible modular deployment strategies can significantly improve the economic performance of large, expensive projects. As sensitivity analyses show, the improvements can be significant over a wide range of analytical assumptions. An important insight is that higher learning rates increase the benefits of flexibility, counteracting the effects of economies of scale. Overall, the study shows that flexibility in engineering design of major production facilities such as LNG plants has multiple, supporting advantages due to uncertainty, learning, and location. © 2015 Wiley Periodicals, Inc. Syst Eng 18: 253–268, 2015

Key words: design flexibility; real options; project valuation; economies of scale; learning; LNG

1. INTRODUCTION

This paper presents an innovative flexibility analysis as a practical, effective procedure to improve the expected value of large-scale, capital-intensive projects when there is market uncertainty. Its novelty lies in its approach and scope. As to approach, it develops understanding of the drivers of the value of flexibility, and thus builds acceptance among decision-makers. As to scope, it explicitly considers the combined effects of uncertainty, economies of scale, learning, and geographic distribution. The approach enables developers to understand how to adapt the system for better performance as its requirements and opportunities evolve over its useful life. It achieves this by exploiting modularity in design [de

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Neufville and Scholtes, 2011; Cardin, 2014]. The study contrasts with other analyses in that it explicitly and innovatively considers the combined effects of uncertainty, the time value of money, economies of scale, learning, and geographic dispersion of demand on the economic benefits of flexibility in design.

The study demonstrates the approach in the context of a case analysis for the design of a liquid natural gas (LNG) production system. This is an important issue, given the increasing role of LNG in energy markets. The advantage of using natural gas products has increased over the last decades, resulting in a considerable growth in demand for LNG. Research has shown that by 2030 the demand for this fuel could be more than three times higher than in 2011 [Kumar et al., 2011].

Increased price differentials between LNG and competing energy sources have stimulated this demand. In 1997, U.S. fuel prices hovered around $20/barrel of oil (West Texas Intermediate—WTI) and $2.50/Million British thermal unit (MMBtu) for Henry Hub natural gas. By 2011, these prices were around $100/barrel for oil and $5/MMBtu for natural gas [GLE, 2011]. While the price of oil rose five times, that of natural gas only doubled, thus making gas much more economically attractive. While the absolute ratio of oil and LNG prices fluctuates substantially, LNG has maintained its relative attractiveness. As of November 2014, the spot prices for oil and LNG were about $80/barrel and $4/MMBtu.

LNG is a physically attractive fuel because it has high energy density and is "green". Its volume is 600 times less than the same amount of natural gas at room temperature while the volume of compressed natural gas (CNG) is 1% less of its original volume [GLE, 2013]. A road truck can go around 800–1,200 km (500–750 miles) on a tank of LNG [GLE, 2011]. Furthermore, new emissions control regulations are increasing the attractiveness of LNG for road transport. Such advantages make LNG a potentially excellent choice for the heavy transportation sector.

The business opportunities for LNG production are economically risky, however. They require substantial initial investments subject to great market uncertainties in the demand for and price of LNG. Initial forecasts are almost certainly wrong. Designs could easily be too large and lose money, or too small and miss opportunities. The issue is: how do we manage such risks? How do we develop the system to maximize expected benefits?

This paper proposes a method to address this kind of issue, that of developing an economically optimal deployment of a large-scale complex system in the face of uncertainty. It leads to the consideration of a design of a flexible system, one that configures the system to minimize possible downside outcomes, while positioning it to take advantage of upside opportunities. The next section discusses the analytic background to flexibility in systems design. Section 3 provides the details of the proposed methodology. Section 4 demonstrates the implementation of the approach, using the case study of an LNG production system. The final section summarizes major findings, providing conclusions and insights for further research.

2. ANALYTIC BACKGROUND

2.1. Flaw of Averages

Basing design and investment decisions on the most likely or average scenario generally leads to suboptimal results. This is because the value resulting from the overall distribution of the uncertainties is not equal to the value associated to the average. Assuming otherwise is to fall for the "Flaw of Averages" [Savage, 2009]. Since systems response are almost universally non-linear, the increased output from an upside scenario (e.g., high demand growth) generally does not balance the lost output from a similar downside scenario (e.g., low demand growth). This mathematical truism is sometimes known as Jensen's Law. Equation (1) captures this formally.

$$f\left(E\left[x\right]\right) \neq E\left[f\left(x\right)\right], \tag{1}$$

Here, *f(E[x])* is the net present value (NPV) associated with the expected LNG demand $E[x]$ (i.e., the time-discounted value of the cash flows generated by the project). This quantity is not equal to the actual expected NPV $E[f(x)]$associated with the distribution of demands (x). In practice, Equation (1) means that the economic evaluation of a design based on the average or expected demand scenario does not correctly value any design, and thus does not correctly identify the best solution.

For example, consider a hypothetical LNG facility: it can produce 1.0 ton per day (tpd) of LNG to supply this expected or average demand forecast, and its value is $NPV\,(1.0) =$ \$ 1.0 million when operating at this capacity. Consider what happens when the actual demand varies from the average, for example if the demand were equally likely to be 0.5, 1.0, and 1.5 tpd. The actual NPV for the lower demand is less than for the design conditions (operating at half capacity), say $NPV\,(0.5) = \$\,0.5$ million. On the other hand, the value for the highest demand would be limited by the plant capacity, and so $NPV\,(1.5) = \$\,1.0$ million. Then the expected value of the facility would actually be:

$$E\left[NPV\right] = 1/3\,(0.5 + 1.0 + 1.0) = \$0.83\text{million}$$

which is less than the value of the average demand, $NPV\,(1.0) = \$\,1.0$ million. This example illustrates the Flaw of Averages and emphasizes the need to consider the entire distribution of uncertainties in order to value projects correctly. The correct expected value of a project may be greater or smaller than that misleadingly estimated using averages of uncertain parameters. The important fact is that it is different, often greatly so.

2.2. Use of Simulation

Monte Carlo simulation is now a usual means to assess the behavior and value of systems subject to distributions of uncertainty [de Neufville and Scholtes, 2011; Cardin, 2014]. Monte Carlo simulation is a general approach that can easily model complex systems under any form of probability distribution, of any shape, continuous or discrete. Monte Carlo simulation provides the freedom to model precisely the detailed attributes of real-world problems, using realistic design variables, parameters and decision rules. In practice, Monte Carlo simulation examines the effects of combinations of the uncertain parameters, taking each at its frequency of occurrence. It thus performs a large number of valuations, routinely well into the thousands. The only real limit to Monte Carlo simulation is computer capacity.

Although simulation of complex systems design can be computationally expensive, advances in computational technology and improved software processes are enabling faster, more efficient, and less expensive analyses [Neches and Madni, 2013]. de Neufville et al. [2006] for example showed how designers of infrastructure systems can evaluate engineering systems using spreadsheet simulations.

From a purely theoretical point of view, practical NPV valuations based on simulation have a distinct weakness. From a theoretical perspective, a correct economic analysis would not use a fixed discount rate, but would adjust it for the degree of risk and uncertainty, using a higher rate when the risk is greater. Procedures for making such adjustments do exist, such as the binomial lattice method using the so-called "risk-neutral" probabilities [Luenberger, 1996]. However these methods are only validly applicable under very specific conditions that are essential for properly defining the relationship between risk and the risk-adjusted discount rate. Specifically, they impose assumptions concerning the existence of a ready, full-information and complete market for the things being valued. The fact is however, that systems engineering projects generally neither exist nor are traded in any market, let alone those satisfying the conditions that appropriately justify "risk-neutral" adjustments. Cardin [2014] provides a detailed discussion of the pros and cons of other approaches to value flexibility in an engineering setting. On balance, despite conceptual drawbacks, the accepted engineering approach values projects under uncertainty using simulation and fixed discount rates.

2.3. Flexibility in Engineering Design

To maximize the value of a project in the context of uncertainty, we must structure projects with the capability to adjust to the evolution of uncertainties over time. The general idea is that optimal system designs generally should have the capacity to avoid the worst risks, and take advantage of favorable opportunities. That is, they should have "real options," defined technically as the "right, but not the obligation," to adjust the system favorably in the face of uncertainty. For example, the spare tire on a car makes it possible to overcome the inability to move after a blowout. Likewise, the provision of extra structural strength in a suspension bridge enables its owners to double-deck it in case of need (as was done for New York's George Washington Bridge, and for Lisbon's 25 de Abril Bridge). That is, designers can improve the economic value of systems under uncertainty by using real options, otherwise known as flexibility in design.

Flexibility in engineering design and its evaluation techniques have evolved in systems engineering practice through adaptation of concepts from financial options analysis (e.g., Black and Scholes [1973]; Cox et al. [1979]) and real options analysis (e.g., [Dixit and Pindyck, 1994, Trigeorgis, 1996]) in ways that suit the needs of engineering design in a highly uncertain world. Thus Browning and Honour [2008] proposed a conceptual approach to quantify the life-cycle value of a system. They concluded that to maximize life-cycle value, we should design systems to facilitate adaptability to changing circumstances and stakeholder preferences. Engel and Browning [2008] complementarily presented quantitative models to assess the value of adaptability of system architecture as a means of maximizing its lifetime value. Fitzgerald et al. [2012] presented a "valuation approach for strategic changeability" (VASC) based upon Epoch Era Analysis (EEA) [Ross, 2006; Ross and Rhodes, 2008] to investigate the value of changeability in complex engineering systems at early stage of the design process.

To make the best use of flexibility we need to know when to exercise our options. Specifically, we need decision rules to guide the use of flexibility. In principle, these could be normative or descriptive. In practice, it has so far only been possible to define normative decision rules for a limited number of situations that are too simplistic for complex systems (e.g., path independent evolution of uncertainties with only one option to exercise, as to exercise a call in a stock market). Decision rules appropriate for most analyses of engineering systems thus descriptively reflect how system operators might actually adapt the system in light of uncertainty realizations. Thus the VASC model has transition rules based on a defined set of change mechanisms. The methodology proposed in this paper embeds pre-defined decision rules in the Monte Carlo simulation. As the choice of the decision rule affects the lifecycle performance of the system, it benefits from guidance and thorough evaluation [Cardin, 2014].

The term "flexibility" has different definitions in different contexts. Some researchers have sought to clarify this meaning to facilitate communication among systems engineering practitioners and academics [Ross et al., 2008; Ryan et al., 2013]. Flexibility in engineering design is certainly an interdisciplinary field for research and practice [de Neufville and Scholtes, 2011; Cardin, 2014]. It adapts the concept of financial options to engineering systems, giving rise to the concept of "real options." The goal is to increase expected economic value by providing the adaptive strategies to respond to uncertainties most profitably [Trigeorgis, 1996].

Flexibility exists "on" and "in" engineering systems. Flexibility "on" systems is associated with managerial flexibility such as abandoning or deferring the deployment of a system until favorable market conditions occur; expanding/contracting/reducing capacity; deploying capacity over time; switching inputs/outputs; and mixing the above [Trigeorgis, 1996]. Flexibility "in" systems refers to technical design components that enable the flexibility to change system capacity or functionality [Wang, 2005]. Cardin [2014] provides a taxonomy and framework to organize design and evaluation activities that enable flexibility in engineering systems.

In sum, flexibility in engineering design enables a system to capture the potential value associated with different scenarios. For instance, it might enable the capture of more demand in cases of high demand, thus increasing the expected economic value (i.e., like a call option). It might reduce financial losses in a downside demand scenario (i.e., like insurance or a put option). Flexibility in design enables desirable changes in configuration (e.g., by increasing capacity as needed) over time and thus increases the cumulative density function of the value of the design.

3. METHODOLOGY

3.1. Overall Concept

The proposed flexibility analysis aims to be an innovative, practical, and effective procedure to identify possible improvements in the expected value of large-scale, capital-intensive projects when there is market uncertainty. Its novelty lies in the way it develops understanding of the drivers of the value of flexibility, and thus helps to build acceptance among decision-makers. In this vein it explicitly brings out the individual and combined effects of uncertainty, the time value of money, economies of scale, and learning.

This paper addresses the following problem: although researchers well understand the value of flexibility, in practice decision-makers have neither appreciated its significance, nor widely accepted the concept. The implicit conversation between the analyst and the decision-maker goes often something like this:

> **Analyst:** Although you have not done so before, we need to look at uncertainties. I have done so. My calculations show that you can expect much improved performance using a novel design.
>
> **Decision-Maker:** Our designs have worked well. Your uncertainties are full of assumptions. I do not understand how it is possible to increase expected value so dramatically. I cannot risk your proposed solution, especially if it costs more, and I may not use the flexibility in the end. [Please go away.]

The point is this: an effective flexibility analysis should not only develop good answers, it must make them credible. To achieve this, it should facilitate understanding of how and why flexibility delivers value. The proposed methodology provides a way to achieve this appreciation.

The methodology builds understanding of the value of flexibility in two ways. The overall approach is to focus individually in sequence on the four elements of the flexibility analysis: the valuation model, the uncertainty analysis, the analysis of specific options for flexibility, and the necessary sensitivity analysis. The detailed part of the analysis examines the specific contributions of economies of scale, discount rate, and learning, and geographic distribution to the value of flexibility, thus helping decision-makers develop a more intuitive understanding of the drivers of value.

Figure 1 illustrates the process. Rather than providing a final overall result as the product of the analysis, the proposed approach explicitly considers and reports on the four principal elements of the flexibility analysis.

- Step 1 establishes the basic Discounted Cash Flow (DCF) valuation model that integrates inputs, constraints, and outputs to obtain the correct total net value of the system for any assumed possible outcomes, properly discounting for the time value of resources. The step then exercises the model for the usual deterministic case of fixed specifications with no uncertainty. This demonstrates the model and provides the base case design.
- Step 2 sets up the uncertainty environment and then applies this context to the base case model using simulation. Unless the system being analyzed is trivial (specifically linear and unconstrained) the value we obtain in this step is different, generally significantly so, from the result obtained for the Step 1 base case. Unless the uncertainties are negligible, this observation shows the decision-maker that the deterministic base case provides an incorrect result, and thus that the design process needs to consider uncertainty. This conceptual result does not depend on the specific form of the uncertainty distribution. It is a simple result of Jensen's Law, Equation (1).
- Step 3 then explores the value of various forms of flexibility. In general (but not necessarily) these involve modules of performance or capacity. The exploration considers how designers can implement these modules both over time (as uncertainty about system requirements resolves) and over space (the "move" alternative). In general, the results of these analyses demonstrate that flexible strategies can lead to significant increases in value compared to the base case design, which is typically more rigid and optimized for the set of initial assumptions.
- Step 4 develops the sensitivity analyses that identify the drivers of the value of flexibility. This process helps the decision-maker understand how and why characteristics of the system and its situation give value to flexibility. This detailed part of the analysis shows how greater discount rates, learning effects, and geographic distribution counterbalance economies of scale in defining the value of flexibility.

Additionally, the proposed approach incorporates the ability to consider different measures of performance, such as NPV, Value at Risk (VaR), Value at Gain (VaG), Standard Deviation of results (STD), and Initial capital expenditures (Capex), which is often a major consideration for investors in risky projects. It also allows the use of procedures to help generate flexibility strategies, such as prompting Cardin et al. [2013a] and the Integrated Real Options Framework by Mikaelian et al. [2011].

3.2. Step 1: Deterministic Analysis

The methodology starts with a deterministic analysis considering a fixed design as benchmark. The aim is to understand the key components of the system that influence its lifecycle performance. In practice, the standard industry performance metric for project evaluation is NPV [Cardin et al., 2013b], but alternatives exist. The NPV is the sum of cash flows of revenues and costs, TR_t and TC_t, over the project life, T, discounted at the rate r, see Equation (2).

$$NPV = \sum_{t=1}^{T} \frac{TR_t - TC_t}{(1+r)^t} \tag{2}$$

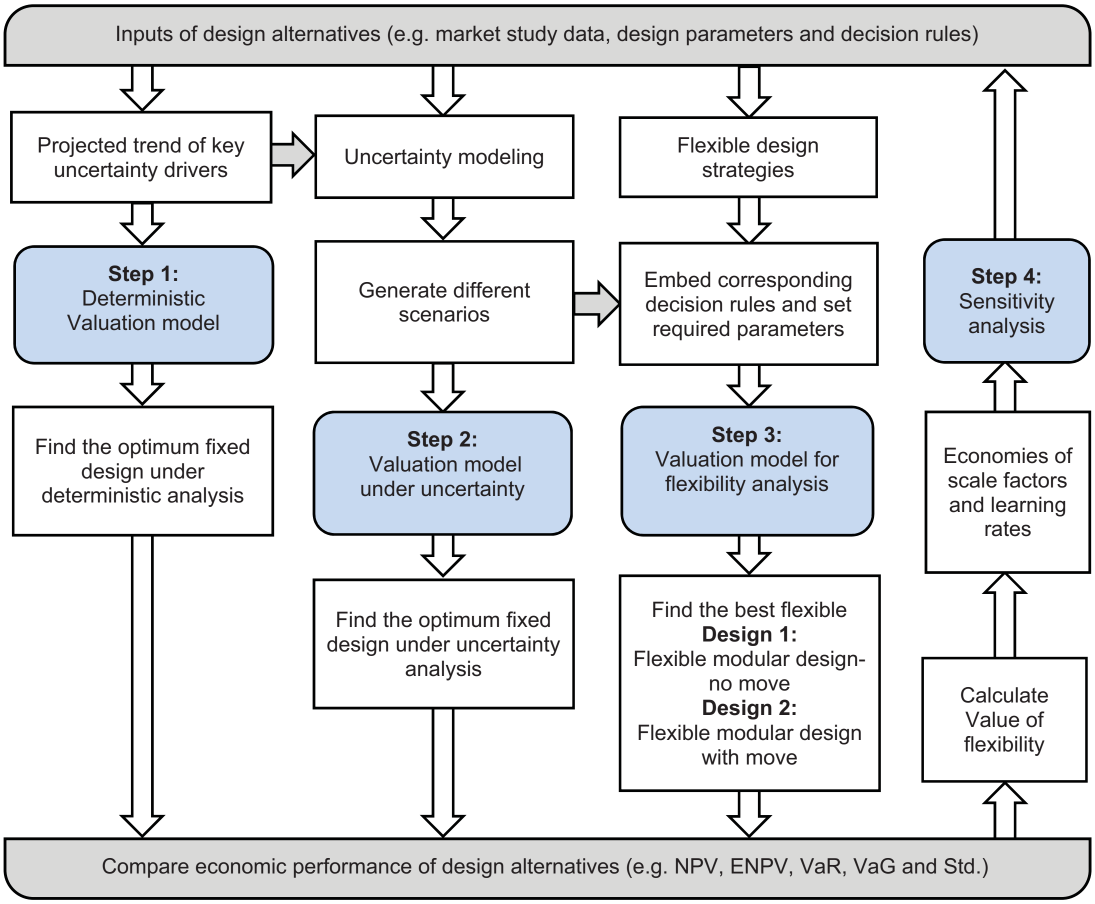

Figure 1. A methodology to evaluate and compare candidate flexible system designs.

Demand for the products of the system is a key driver of its performance. It is possible to model demand in many ways, and analysts should choose the model appropriate for the situation. For example, in the case of a new product an s-curve function may be most reasonable (3), reflecting initial low demand, followed by a period of rapid growth, that eventually tapers as it approaches saturation. In this case, M_T^D is the maximum expected demand; b^D is the sharpness parameter that determines how fast demand grows over time to reach the upper bound for demand, and a^D defined in Equation (4) translates the curve horizontally over the time axis.

$$D_t^D = \frac{M_T^D}{1 + a^D e^{-b^D t}} \tag{3}$$

$$a^D = \frac{M_T^D}{D_0^D} - 1. \tag{4}$$

3.3. Step 2: Uncertainty Analysis

This step models the major uncertainty drivers and analyzes their effect on lifetime system performance. The analysis uses the distribution of input parameters over time to calculate the distribution of the performance metric. Each demand scenario s leads to a performance outcome, $\mathrm{NPV_S}$. Simulation is the conventional way to do this, but analysts can use different techniques (e.g., decision trees, binomial lattice).

We create a stochastic version of demand using uncertainty factors. The case study used the s-shaped model of demand. As in Equation (5), M_T^U is the stochastic demand limit and b^U is the stochastic sharpness parameter in the demand model under uncertainty. Equation (6) defines a^U as the stochastic translation factor that varies due to volatilities in initial demand (i.e., D_0^U) and demand limit. Realized demand at time $t+1$ equals realized demand at time t plus annual volatility multiplied by growth rate G_t at time t, as in Equation (7). While other assumptions are possible, it is convenient to assume that G_t follows a standard normal distribution and Av is a fixed parameter calibrated using historical data.

$$D_t^U = \frac{M_T^U}{1 + a^U e^{-b^U t}} \tag{5}$$

$$a^U = \frac{M_T^U}{D_0^U} - 1 \tag{6}$$

$$D_{t+1}^U = D_t^U + (Av \times G_t). \tag{7}$$

The uncertainty analysis results in a distribution of possible performance outcomes. The obvious way to compare this result to that of the deterministic model is to focus on the expected value of the distribution of NPV, or ENPV, calculated according to Equation (8). As per Equation (1), the overall result is that the ENPV does not equal the deterministic NPV, which makes the point that the deterministic analysis that ignores uncertainties may lead to an erroneous result.

$$\mathrm{ENPV} = \frac{1}{N} \times \sum_{s=1}^{N} NPV_s. \tag{8}$$

Note that the ENPV metric implies risk neutral preferences, which may not always be appropriate. Indeed, decision-makers often take downside risk into account and weight it heavily. It is thus often useful to supplement the ENPV metric with others that represent the extreme distributions of the outcomes, such as the VaR (e.g. expressed as 5$^{\text{th}}$ percentile of the distribution or P5) for a given level of probability and, complementarily, the potential for upside gain, the VaG (e.g. expressed as 95$^{\text{th}}$ percentile or P95). More sophisticated multicriteria decision-making approaches are also available when it is desirable to consider both quantitative and qualitative criteria [Georgiadis et al., 2013].

3.4. Step 3: Flexibility Analysis

Building on Step 2 that quantitatively demonstrates the existence of risks, Step 3 addresses the issue of risk management. Specifically, it recognizes that system operators can change, adapt, and reconfigure the system in light of how they see events happen over time, of how they see uncertainty resolve. It thus explores ways system designers can reduce risk and increase opportunities. This can be done using prompting mechanisms in a systematic series of questions in discussions with collaborating field experts, to tease out the main uncertainty drivers, and thus generate the flexibility strategy and decision rules [Cardin et al., 2013a]. Alternatively, if the range of possibilities is obvious, one can explore the space of possible flexible solutions using screening models or enumeration techniques.

A standard approach to enable flexibility in design is to build the system in modules, starting small and expanding as appropriate. The possible advantage of this approach is intuitive: building small at the start means that there is less to lose; being able to expand as desired makes it possible to take advantage of opportunities as and to the extent they emerge.

3.4.1. Economies of Scale

The degree of economies of scale is a most important system characteristic as regards flexibility in design. Economies of scale refer to the possible phenomenon that the average cost per unit of capacity decreases with larger total capacity. Economies of scale characterize many systems. Crudely speaking, they prevail in systems whose capacity is proportional to volume and whose cost is proportional to enclosing surface: ships, aircraft, chemical plants, thermal power plants, pipelines, and such. Economies of scale are important because they drive designers toward the largest facilities, typically intended to cater to future demands far into the future. That is, economies of scale encourage immediate commitments ahead of possible demand—and thereby discourage flexible designs that might, for example, involve a modular approach to capacity deployment using a series of smaller increments [de Neufville and Scholtes, 2011].

The so-called cost function in Equation (9) provides a common representation of the phenomenon of economies of scale. The parameter α is the economies of scale factor: the lower α is, the greater the economies of scale. Given the implications of economies of scale for flexibility in design, the sensitivity analysis should pay attention both to determining the α scale factor for a system, and to exploring its implications for the design.

$$\text{Capex of a fixed plant} = \text{capacity}^{\alpha}. \tag{9}$$

3.4.2. Time Value of Money

The discount rate r reflects the time value of money and is a key factor in the DCF valuation process. It properly discounts the value of future benefits and costs, compared to current investments—as in Equation (2). As regards flexibility analysis, it provides a counterbalance to economies of scale. Because it reduces the present cost of future investments, it increases the relative attractiveness of a design strategy that defers the cost of future additions to capacity, as by modules. Manne [1967] discusses the tradeoffs between the economies of scale and the time value of money in great detail.

3.4.3. Learning Rate

The learning rate refers to the descriptive fact that the cost of modular capacity routinely decreases with the number of units produced. This is a common observation: when we do something for the first time we are relatively inefficient; the more we repeat the task, the more we learn to be productive. Hence the appellation of "learning" for the phenomenon, even though in practice the cost reductions may also come from design innovations and manufacturing improvements. Equation (10) represents this situation, where U_1 and U_i are the Capex of the first and ith modules, and B is the slope of the learning curve determined empirically from case studies [de Neufville and Scholtes, 2011]:

$$\mathrm{U_i} = U_1 \times i^{B}. \tag{10}$$

The slope B is calculated with empirical values of learning rate (LR%), as Equation (11) shows.

$$\mathrm{B} = \log(100\% - LR\%)/\mathrm{Log}\,(2)\,. \tag{11}$$

The learning phenomenon encourages the use of modular flexibility, as does the time value of money and for the same reason: it counterbalances potential economies of scale by making the cost of small modular increments of capacity more economical compared to large units. A good sensitivity analysis for flexibility will investigate the degree of the learning effect.

3.4.4. Geographic Dispersion

Geographic dispersion of the demand for a system product is another driver favoring flexibility in design. The intuition is direct: if demand is far away from a central point of supply, then the distribution of modules of capacity to the points of demand can reduce transportation costs, and overcome possible extra unit costs of capacity associated with smaller modules. Designers should also investigate this possibility.

3.4.5. Decision Rules

To account for system flexibility, the analysis embeds decision rules into the DCF model under uncertainty. These rules both state the conditions under which system operators would choose to take action, and implement the decisions in the model. For example, to embed a flexible capacity expansion policy in an Excel® spreadsheet DCF model under uncertainty, we insert IF statements to test for conditions, whose responses trigger actions such as the addition of capacity at a given cost and at a specified time. Specifically, a decision rule for capacity expansion could be: IF "*observed aggregate demand in the current year is higher than a threshold value*" THEN "*implement extra modular capacity in next year"* ELSE *"do nothing*". The threshold value determines when the designer should build extra capacity. For example, decision-makers may decide to add capacity as soon as the difference between the realized and current capacity (i.e., unmet demand) reaches X% of existing capacity.

3.4.6. Value of Flexibility

The value of flexibility is the difference between the overall system value with flexibility and that without flexibility as calculated in Step 2, as Equation (11) indicates.

$$\text{Flexibility Value} = \max(0, \text{ENPV}_{\text{Best Flexible design}} - \text{ENPV}_{\text{Optimum fixed design}}). \qquad (12)$$

3.5. Step 4: Sensitivity Analysis

The primary role of sensitivity analysis, as concerns flexible design, is to investigate the stability of the design decision. Indeed, once we recognize that we cannot accurately predict future demands on a system, we have also acknowledged that we cannot define future performance precisely. The important matter under these circumstances is to see how the analysis has led to the preferable design, given the range of uncertainties. The sensitivity analysis seeks to determine the range of assumptions (e.g., model parameters) over which an optimal design is still preferred or, conversely stated, at what point the choice of solution might change. The proper role of sensitivity analysis for design under uncertainty is to ascertain whether the choice of design is robust.

The proposed method thus conducts sensitivity analyses on key drivers of value, to explore how different assumptions about system parameters might change decisions. Naturally, this sensitivity analysis focuses on the parameters that are least knowable (such as future demands), and that are the focus of this study (such as economies of scale and learning rates). The overall purpose is to investigate the robustness of the optimal design and its sensitivity to key uncertain parameters.

4. DEMONSTRATION USING LNG CASE STUDY

4.1. Objectives

The prime objective of this section is to demonstrate the use and value of the proposed methodology. We do this by applying it to an important current issue: the development of an LNG production system for road transport fuel. The application follows the four-step analysis presented in the previous section. The result shows how the method can discover, evaluate, and justify intuitively significant increases in value using flexible design. The application also serves a second objective, which is to illustrate potential flexible strategies for LNG production. The emphasis here is on "potential strategies." While the data used are representatively realistic for the location considered at the time of analysis, these numbers naturally differ from those appropriate in other places at other times. The results obtained illustrate specific strategies worth considering in the development of an LNG production system and, by extension, more widely to petrochemical production systems.

4.2. Description of LNG Case

As the Introduction indicates, the production of LNG is becoming a salient issue worldwide due to the growth of natural gas supply, and of the demand for this relatively inexpensive "clean" fuel with high energy density. However, the deployment of a large-scale LNG production system is economically risky, in view of the great uncertainty in future demand. The overall questions are: What is the most economically valuable strategy for deploying an LNG production and distribution system? How do we design it in the face of uncertainty?

The LNG supply chain links exploration, extraction, liquefaction, transportation, storage and regasification. It has many versions, as there are different upstream resources and liquefaction processes (e.g., gas wells and plants onshore or offshore), and different end users (e.g., power plant, home use and transportation sector). Research in this area has studied the coupled segments of large-scale shipping and receiving terminal of an LNG supply chain to minimize cost and storage inventory, while maximizing the output of natural gas to be sold Özelkan et al. [2008]; tactical planning to optimize the LNG inventory routing problem Grønhaug and Christiansen [2009]; and transportation planning and inventory management of a LNG supply chain used in tactical planning during negotiations about deliveries to different regasification terminals and annual delivery plan used in operational level decision making Andersson et al. [2010].

Designers need to evaluate LNG production systems in the early stages of design, in particular to consider strategic level decisions involving flexibility and uncertainty in the analysis of site production capacity and deployment over time. In addition, to these authors' knowledge there has been no study of the combined effects of economies of scale, time value of money, learning, and geographic dispersal of the system configuration. By investigating the effects of these strategic factors affecting the design of LNG production systems, this application offers a contribution to the understanding of this opportunity.

This study investigated the proposed design and deployment of a LNG production and distribution system providing fuel for highway trucks. Its scope within the LNG supply chain is from the on-shore delivery of natural gas, through its conversion into LNG through liquefaction at a main production site, to its distribution to end users at five geographically dispersed demand sites equipped with filling station facilities. All sites have access to the pipeline network distributing the natural gas.

Figure 2 schematically represents the three alternative design configurations of the LNG production and distribution system. In each case, fuel trucks carry the LNG produced at the main production site to the five demand sites. The designs differ in the way they deploy capacity over time and space:

- Figure 2(a) represents the conventional design that creates an optimal single large facility taking advantage of economies of scale. It is the fixed design.
- Figure 2(b) represents a flexible strategy that deploys capacity at the central site according to how demand does or does not grow over time. It is the "flexible strategy—no move."
- Figure 2(c) is a more flexible strategy that allows for gradual deployment of capacity both over time and geographically to the demand sites. It is the "flexible strategy—with move."

4.3. Parameters for LNG Case

Domain experts in LNG plant design and distribution developed the following parameters for the study:

- The time needed to build LNG capacity is 3 years at the main production site, 2 years for the first modular plant at each demand site, and 1 year for any modular addition to existing capacity.
- The Capex cost of building a 25tpd capacity LNG plant module is \$25 million. The Capex of larger plants scales according to Equation (9). The extra cost of any first capacity deployment at each demand site, due to the expense of tie-in to the natural gas pipeline and extra land, is 10% of the Capex.
- The analysis examined economies of scale: $\alpha = 1$, 0.95, 0.9 and 0.85. The modular design analysis investigated learning rates corresponding to LR = 0%, 5%, 10%, 15%, and 20%.
- The Opex operating cost of a plant is 5% of its Capex. The transportation cost for distributing LNG from the central production site is \$0.4 per ton-kilometer, over the 118, 121, 281, 318, and 446 km distances to the demand sites.
- The economic assumptions are: project lifetime = 20 years; corporate tax rate = 15%; and depreciation is straight-line over 10 years with zero salvage value.
- Management stated that the discount rate should, in this case, be taken as 10%.
- Demand is identical over the five demand sites; there is no market at the main production site.

Realistically, future demand over the 20-year life of the project is highly uncertain due to currently unknown prices, competition, government regulations, and other factors. Market research at the collaborating firm provided the deterministic and stochastic LNG demand modeling parameters summarized in Table I. While other types of distributions such as Normal and Lognormal are possible, it is convenient to assume that D_0^U, b^U, and M_T^U follow a uniform distribution; where Δ_{D_0} is the limit on volatility of the realized demand in year 0 as it differs from its projected value; Δ_b defines the volatility of the sharpness parameter as it differs from its forecasted value.

4.4. Step 1: Deterministic Analysis

The deterministic analysis determined the optimal size of the central plant for a fixed forecast of the LNG demand. It calculated the value of each of the plants consisting of 25 tpd modules of capacity. It did this for the range of economies of scale, from none ($\alpha = 1.0$) to the highest assumed ($\alpha = 0.85$).

Figure 3 graphs the results. The intuitive understanding is that:

- There is a design "sweet spot" for the optimal plant size (the stars on the curves) for any level of economies of scale; build too small, and there is no profit from higher demands—build too large, and there is overcapacity and attendant lower values.
- The greater the economies of scale (smaller α), the larger the fixed design should be. This because the economies of scale lower the average unit cost of capacity and thus favor larger designs.

4.5. Step 2: Uncertainty Analysis

The uncertainty analysis focused on the distribution of possible demand for LNG over time. Based on the demand parameters from market research in Table I, it used Monte Carlo simulation to develop sequences of demand patterns over the projected life of the project. Figure 4 compares the projected deterministic LNG demand with 25 representative demand scenarios. The large deviations between best estimate and possible scenarios are as expected for long-term forecasts for new technologies in new markets [de Neufville and Scholtes, 2011].

The analysis determined the optimal designs under uncertainty by valuing each of the possible designs, as for the

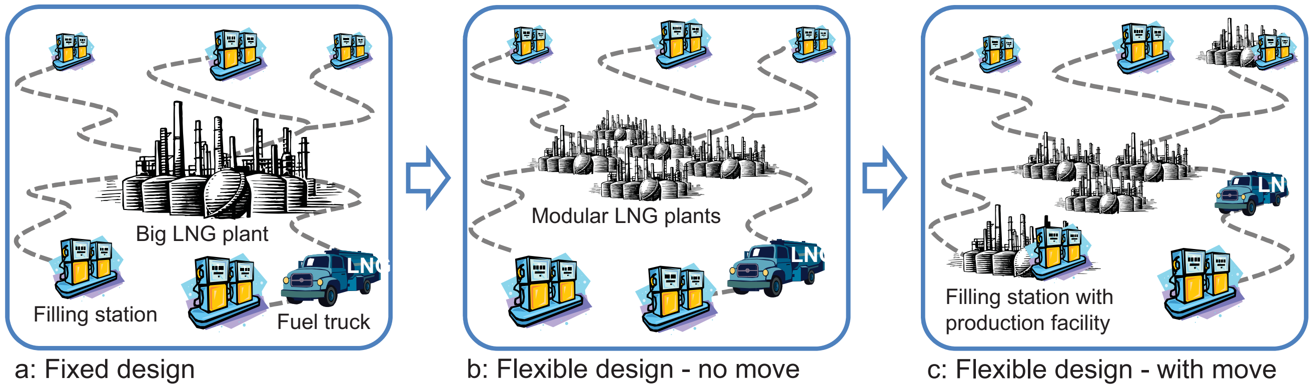

Figure 2. Alternative design configurations of the LNG production and distribution system.

Table I. Parameters Used in Deterministic and Uncertain Demand Modeling

Deterministic demand model		Stochastic demand model		
Parameter	Value	Parameters ~ Uniform distribution	Volatility	Value
D_0^D	5 tpd	$D_0^U \sim$ Uniform $(D_0^D(1-\Delta_{D_0}), D_0^D(1+\Delta_{D_0}))$	Δ_{D_0}	50%
b^D	0.35	$b^U \sim$ Uniform $(b^D(1-\Delta_b), b^D(1+\Delta_b))$	Δ_b	70%
M_T^D	50 tpd	$M_T^U \sim$ Uniform $(M_T^D(1-\Delta_{M_T}), M_T^D(1+\Delta_{M_T}))$	Δ_{M_T}	50%

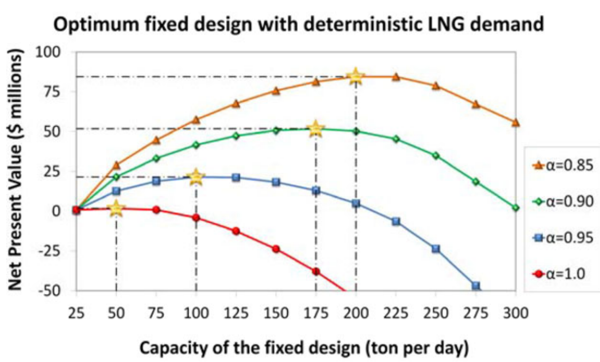

Figure 3. NPV of fixed designs under deterministic demand. Stars show the optimum design for a given economies of scale factor.

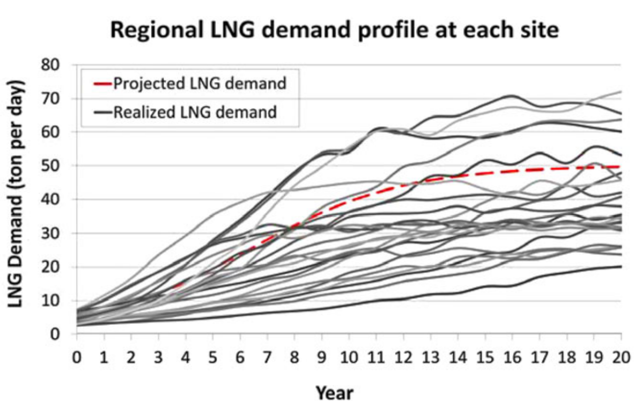

Figure 4. Projected deterministic demand (dashed line) compared to twenty-five realized scenarios.

deterministic case. The value of each possible design was a distribution associated with the possible demand scenarios. Because of the non-linearities within the system, inherent in both its cost structure and the variations in demand, the shape of the distribution of values differs from the distribution of demand. To ensure comparability, the analysis valued each design using the same set of demand scenarios. It relied on 2000 scenarios to develop distributions of value stable estimates of the distribution of performance.

The results of the uncertainty analysis differ systematically and significantly from those of the deterministic analysis (Table II). Most obviously, as expected from Jensen's Law in Equation (1), the values of the optimal designs are different. Specifically the project values for any level of economies of scale are lower. This is due to the fact that capacity-constrained systems do not benefit from excess demand, but do lose when the demand is less than anticipated, resulting in lower overall value (as the example in Section 2.1 illustrates).

Moreover, the uncertainty analysis leads to systematically different optimum designs than the deterministic case. In this example, the optimum fixed designs for the uncertain demand are all systematically smaller than those suggested by the deterministic analysis. This is due to the lower project values that occur once the analysis takes uncertainty into account.

The analysis that properly accounts for uncertainty thus demonstrates that the results of a deterministic analysis are systematically incorrect. They are often doubly so, first by providing incorrect estimates of value, and second by possibly recommending designs that are in fact not optimal. [Exceptions to this pattern do occur, principally when there is little uncertainty or if the systems responses are trivially linear.]

Table II. Optimum Fixed Designs Under Deterministic and Uncertain LNG Demand with Different α

	Optimum capacity (tons/day)		Optimum NPV value ($ millions)	
Economies of scale factor, α	Deterministic Analysis	Analysis with Uncertainty	NPV if Uncertainty Ignored	ENPV recognizing Uncertainty
1.0	50	25	1.75	0.87
0.95	100	75	21.51	14.27
0.90	175	125	51.75	37.18
0.85	200	175	84.56	61.18

4.6. Step 3: Flexibility Analysis

The flexible strategy in this example case was to deploy capacity in modules according to proven demand. The idea is to build less capacity at the start—to avoid over commitment and over capacity, and to add capacity modules according to demonstrated demand. In this case, field experts indicated that available standard module had a capacity of 25 tpd. Key to this flexibility strategy, of course, is that the original design enables easy capacity expansion. Providing this capability typically comes at a cost. In the example, the analysis took this cost to be that of tying in the first capacity addition to the gas pipeline.

The analysis considered two kinds of capacity expansion:

1. Incremental capacity addition at the main production site [the "no move" option].
2. Placing additional modules at demand sites to lower transportation costs [the "move" option].

The operational question is: when should we make use of the flexibility to expand? Given the uncertainty in the evolution of demand, there is no a priori absolute answer to this question. In practice, we want to expand capacity when demand has grown sufficiently. Thus the operational issue for the analysis is to determine, for each scenario, when the growth meets the criteria to justify extra capacity. In a Monte Carlo simulation running period by period using Excel, we do this by examining the growth path in previous periods. The analysis solves for the best criteria for triggering expansion by exploring the possibilities, easily by simple enumeration.

A decision rule incorporates the above to answer the operational question of when to exercise flexibility. In Excel, decision rules consist of logical IF/THEN/ELSE operators. For the simple case of capacity expansion only at the primary production site [the "no move" option], the decision rule was:

- IF "the difference between the observed aggregate demand and current capacity at this site is higher than X% of the capacity of the module in the previous period,"
- THEN "expand current capacity by adding a module,"
- ELSE "do nothing."

The values that trigger action in the decision rules, such as the X above, are the "threshold values." For this case, enumeration indicated that the threshold value X = 80% delivered the best system performance.

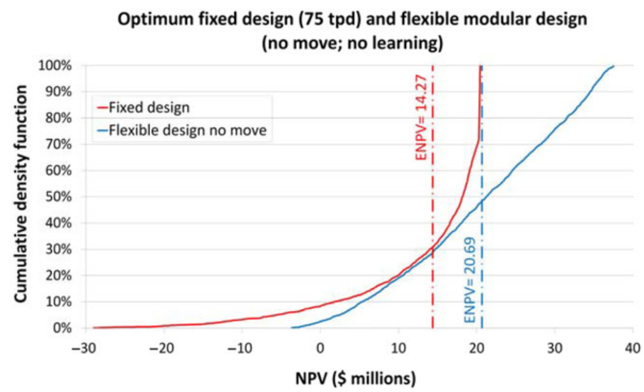

Figure 5. Target curves for the optimum fixed design ($\alpha = 0.95 \rightarrow 75$ tpd) and for the flexible modular design [no move option].

4.6.1. Exploring Design Space with Enumeration

As different decision rules lead to different outcomes, the question arises: what is the best decision rule for the circumstances? Taking advantage of the fact that spreadsheet evaluations run quickly, we solved for the optimal decision rule by comprehensive enumeration.

Table III details the elements of a flexible design vector whose combination defines the space searched by enumeration. It comprises both design variables describing the system architecture, and threshold values of the decision rules. As the second column indicates, the size of the enumeration space increases dramatically with the complexity of the decision rules. The fourth and fifth columns show the values investigated for each variable and the incremental step size, which determines the level of precision used in the enumeration. For the simpler "no move" option, the total number of possible flexible design configuration was 12 [= 2×6]. The more complex "move" option entailed more threshold values and thus a total of 1,980 [= 12×5×3×11] combinations.

4.6.2. Flexible Modular Design—No Move Option

Figure 5 illustrates a typical result of the flexibility analysis. It compares the performance under uncertainty of an optimal fixed design and a flexible design that expands capacity at the main production site ["no move" option]. Specifically, Figure 5 displays the cumulative distribution of the performance of each design (that is, the target curve). The

Table III. Characterization of the Enumeration Space

Option	Design variables	Units	Step Size	Values	Steps
No Move only	Initial capacity	Tons/day	25	0, 25	2
	Capacity expansion threshold, at main production site	% of modular design	20	0 to 100	6
Additions with Move	Moving value threshold	% of modular design	50	100 to 300	5
	Coverage distance threshold	km	100	200, 300, 400	3
	Capacity expansion threshold, at demand site	% of modular design	10	0 to 100	11

lower left side of each curve indicates the lowest level of performance of each design as observed in the simulation, which is at 0% on the vertical scale of the cumulative distribution. The curve extends to the upper right, where it indicates the maximum performance observed, at the 100% level of the cumulative distribution. The curve for the fixed design has an ENPV of \$14.27 million if the system exhibits modest economies of scale ($\alpha = 0.95$), as indicated in Table II. Notice that this fixed design, that takes advantage of economies of scale to build a large facility at the central site, has two unattractive features:

- It can lead to large losses (NPV < – \$25 million), this is because the big plant can lose a lot if sufficient demand does not materialize; and
- Has limited upside potential (NPV < \$21 million), since its fixed capacity cannot serve highest demands.

The flexible design does significantly better than the fixed design, with the same assumed range of uncertainties:

- Its ENPV = \$20.69M (see Table IV), that is nearly 45% better than that of the fixed design [\$20.69 million vs. \$14.27 million]!
- Moreover, the performance of the flexible design in this case dominates stochastically that of the fixed design (i.e., its cumulative or target curve is absolutely to the right of that of the fixed design).
- The flexible design reduces exposure to downside risks: the strategy of building small at first puts less investment at risk and lowers maximum losses if demand is low. In this particular example the flexible design strategy reduces the maximum loss from about – \$25 million to no less than – \$5 million.
- Similarly, the flexible design provides the ability to take advantage of upside opportunities: it enables the easy addition of capacity when demand soars and increases the maximum gain, in this case from about \$21 million to nearly \$38 million.

4.6.3. Flexible Modular Design—Move Option

The flexibility analysis for the "move" strategy, which allows flexibility both as to when and where to add capacity, is similar to the previous example. However, this analysis had to implement additional decision rules to explore this flexibility, to address three questions: when should we build the modular plant for the first time at distance, where should we build it, and when should we expand it?

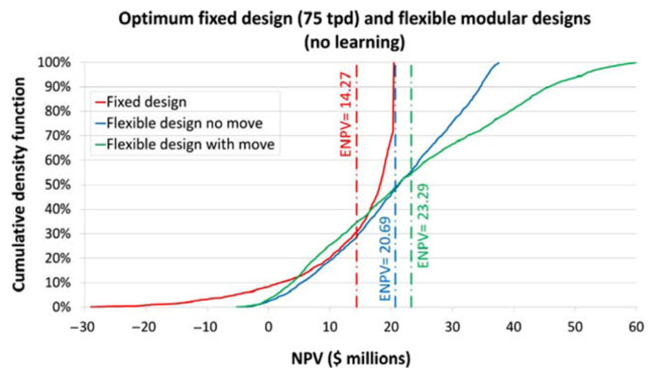

Figure 6. Target curves for the optimum fixed design ($\alpha = 0.95 \rightarrow 75$ tpd) and for the flexible modular designs.

The decision rule regarding the capacity expansion at a distance was:

- IF "*demand at each demand site reaches Y% of the modular design capacity in the previous period*",
- THEN "*build a modular production plant at the demand site*",
- ELSE "*do nothing*".

Comprehensive enumeration determined that in this case the optimal economical threshold value was Y = 100%.

The decision rule regarding the geographical location for capacity expansion was:

- IF "*the demand sites qualified for the first capacity deployment in terms of timing are located beyond the maximum distance D*",
- THEN "*consider building the first modular production facility at those sites*",
- ELSE "*do nothing*".

Again, enumeration determined the best threshold distance as D = 400Km.

The decision rule to build extra modular plants at any demand site was:

- IF "*unmet demand (i.e., the difference between the observed demand and the current capacity at the site) reaches Z% of the modular capacity*",
- THEN "*deploy extra modular capacity*",
- ELSE "*do nothing*".

Further enumeration found the optimal $Z = 50\%$.

Figure 6 and Table IV show the additional advantages of the flexibility to locate capacity away from the main site.

Table IV. Improvement of Multi-Criteria Performance Metrics Due to Flexibility with no Learning ($\alpha = 0.95$)

	ENPV Value ($ millions)			Improvement (%)	
Criterion	Optimum fixed design	Flexible no move	Flexible with move	Flexible no move	Flexible with move
ENPV	14.27	20.69	23.29	45	63
$VaR_{10\%}$	1.82	5.40	3.74	197	105
$VaG_{90\%}$	20.46	34.54	45.78	69	124

As must be expected, looser constraints on system design increase maximum potential value. In this case, the ability to distribute capacity across the region (and thus to reduce logistical costs) further increases system ENPV, in this case from $20.69 million to $23.29 million, and the maximum NPV from about $38 million to about $60 million.

This flexibility and added value, however, complicates the evaluation! In this case, the design with the flexibility to move capacity away from the main site does not dominate stochastically the design that fixes capacity there. Visually, the target curve for the design with the move option crosses the target curves for other designs. In this case, as often happens, designers may not want to choose the solution based upon a single metric such as ENPV. Indeed, no one metric is sufficient to characterize a general distribution. In this context we need to consider multiple criteria of evaluation.

Table IV provides a multi-criteria display of the performance of the fixed and flexible designs. It displays the average ENPV value and two measures of the extreme values. In terms of extremes, better practice generally focuses on some threshold level of cumulative performance rather than on the absolute maxima and minima values from the Monte Carlo simulation. This is because those highest and lowest values, being very rare, can vary considerably between simulations. The threshold values are quite stable, however. Standard thresholds of value are $VaR_{10\%}$, the 10% Value at Risk, the performance at the 10% cumulative probability or percentile, and $VaR_{10\%}$, the 90% Value at Gain. Table IV compares the performance of the fixed and two flexible designs in these terms.

4.6.4. Effect of Learning

Learning increases the value of flexibility. Because it reduces the cost of modules as more get implemented, it favors their use and thus increases the value of flexibility. Figure 7 shows how this occurs. It compares the target curves for the flexible design "no move" option at various levels of learning, from none (LR = 0%) to 20%. The message is clear: the greater the rate of learning, the more valuable the flexibility using modules.

4.6.5. Multi-Criteria Decision-Making

Decision-makers can base their choice of preferred design alternative on many criteria. Table V illustrates the situation. It compares results for the optimum fixed and flexible designs (with and without move), with modest economies of scale and learning rate ($\alpha = 0.95$, LR = 10%). It reports the project values using common economic metrics for project evaluation under uncertainty. In addition to the Expected Net Present Value, these include measures of the shape of the target curve in terms of the dispersion of the results: the 10% Value at Risk, the 90% Value at Gain, and the Standard Distribution. Many investors also pay great attention to the initial Capital Expenditure of projects, when these are most risky. Table V highlights in bold the best values for each criterion. As often happens, different projects appear best according to different criteria. Indeed, the fixed design has the lowest standard deviation and thus might be labeled most "robust"; this could be considered a good thing, but here merely indicates that the fixed design performs uniformly poorly, as it cannot take advantage of upside opportunities. In general, decision-makers have to balance criteria. In this case, the flexible-move design appears best.

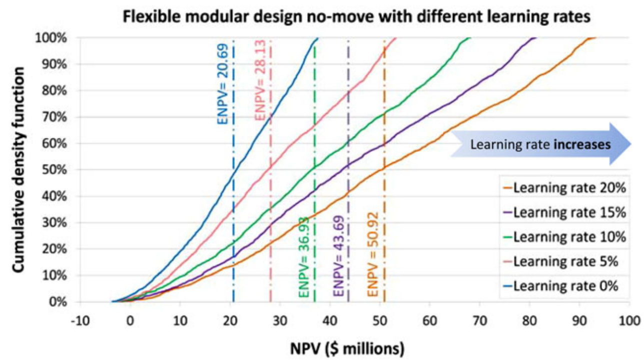

Figure 7. Target curves for flexible modular design [no move] in terms of different learning rates.

4.7. Step 4: Sensitivity Analysis

The proper role of sensitivity analysis for a design under uncertainty is to explore the robustness of the choice of design. As Section 3.5 indicates, once we recognize that we cannot accurately predict future demands on a system, we have also acknowledged that we cannot define future performance precisely. The key question is: is the recommended design robust to variability in parameter estimation? This is the focus of the sensitivity analysis section. Since this paper proposes an approach to improved design, rather than a specific solution to a particular issue, the following paragraphs focus on illustrating the approach to sensitivity analysis for flexibility in design. They do not try the justify the details of the particular design

Table V. Multi-Criteria Decision-Making Table ($\alpha = 0.95$, LR = 10%, figures in $ million)

Criterion	Fixed design	No move option	Move option	Value of flexibility	Best design
ENPV	14.27	36.93	**43.17**	28.90	Move
VaR, 10%	1.82	10.82	**11.06**	9.24	Move
VaG, 90%	20.46	63.17	**80.09**	59.63	Move
STD	**8.78**	18.91	25.31	0.00	Fixed
Capex	60.44	**27.50**	**27.50**	32.94	Flexible

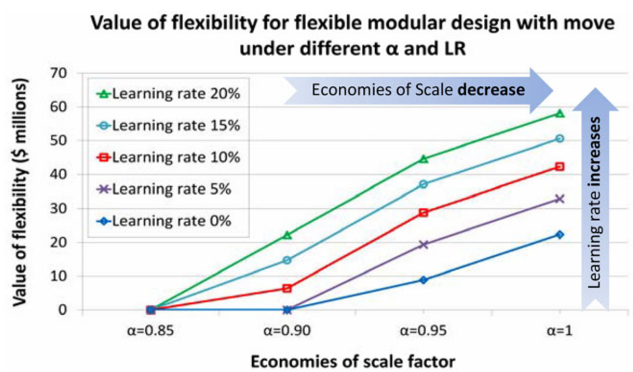

Figure 8. Value of flexibility with different economies of scale and learning rates.

that emerged from the case study analysis, which depended on the specific assumptions deemed appropriate by a company at a given moment. The case study is used to illustrate the effects of important parameters and tradeoffs.

4.7.1. Effect of Economies of Scale and Learning Rate on Choice of Flexible Design

As the analysis stresses, the discount rate and intensities of economies of scale and learning rate have an important effect on the desirability of flexible designs. In the practical context of this demonstration case, we could reasonably assume that the proposed contractor knew its acceptable discount rate, so the effect of this parameter was not investigated. Thus one focus of the sensitivity analysis is on the joint effect of the economies of scale and learning rate factors. Although experienced designers in a particular field can reasonably estimate these factors, they cannot know them unambiguously.

The sensitivity analysis explored the joint effect of various economies of scale and learning rate by repeating the analysis for combinations of these parameters. Figure 8 displays the results. It brings out two important results:

- As expected, lower economies of scale and greater learning rates increase the value of flexibility. Expressed another way, high economies of scale favor larger fixed designs.
- The value of flexibility in this example case ranged up to $60 million, compared to the maximum ENPV of $61.18 million for the fixed design under uncertainty. Flexibility thus clearly offers significant potential that demands exploration.
- In this example case, the flexible design strategy is valuable for all but the most extreme cases, that is, where the economies of scale are particularly high and there is no learning. For even modest learning rates and economies of scale, the flexible modular design is valuable overall. One may thus conclude that, in the demonstration case, the modular flexible design is robust over a wide range against variations in these parameters.

4.7.2. Sensitivity Analysis to Identify the Key Demand Parameter

The most effective sensitivity analyses consider the joint effect of the variability of a parameter and their effects. This contrasts with the approach often encountered in practice of varying each parameter by a fixed percentage (such as +/– 10%). The reality is that some parameters are more uncertain than others. Also, some parameters may not vary considerably, yet have great effect – while others can vary considerably but have little effect. The cost-effective approach to sensitivity analysis then first estimates the plausible range of the spread of these parameters (such as their standard deviation if available) and then calculates the possible effect on the outcomes. The sensitivity analysis then focuses on the parameters with the greatest impact.

Figure 9 illustrates the first result of this approach. It shows the calculated effect of probable ranges of values for the parameters of the assumed demand projection, specifically of its initial and final levels and of the rate of growth. It presents the results in the form of a "Tornado" diagram, which stacks the parameters with the most effect at the top, thus presenting an image reminiscent of the cone of a tornado. For the example case, this first stage of sensitivity analysis indicates that the most sensitive assumption concerns the sharpness factor, whose effect we then examined in detail.

4.7.3. Effect of Key Demand Parameter

Based upon the first stage of the sensitivity analysis that highlighted the importance of the sharpness factor on the evaluation, we examined its effect on the design evaluations for combinations of economies of scale and learning rate. The result was very similar to that of Figure 8: changes in the sharpness factor shifted the lines up and down. Importantly, however, they did not alter the fundamental conclusion: the flexible modular provides the best value over the range of likely combinations of reasonable economies of scale and

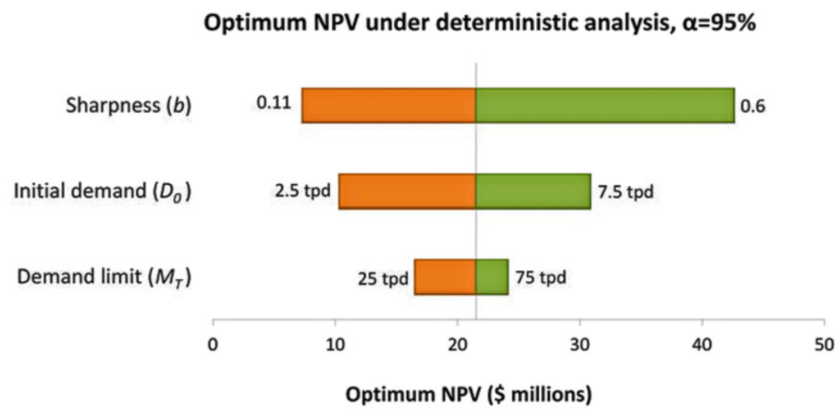

Figure 9. Tornado diagram showing effects of demand parameters on the optimum NPV (fixed design, deterministic analysis, $\alpha = 95\%$).

learning. In these cases, the flexible modular design is indeed robust.

5. CONCLUDING DISCUSSION

This paper presents an innovative flexibility analysis as a practical, effective procedure to improve the expected value of large-scale, capital-intensive projects when there is market uncertainty. Its novelty lies in its approach and scope. Its approach develops an understanding of the drivers of the value of flexibility, and thus builds acceptance among decision-makers. The scope explicitly considers the combined effects of uncertainty, economies of scale, learning, and geographic distribution.

The proposed methodology is a "systems engineering approach" suitable to the reality of design practice. It differs from financially derived real options analysis using arbitrage-enforced and risk-neutral valuation. Two reasons drive this choice. Most importantly, many assumptions crucial to the financial approach are inappropriate to the context of systems engineering. Specifically, we cannot assume path-independence for the different states of the system, since managers do reconfigure systems over time. Further, there are often no reasonable comparables or markets for systems designs, so that crucial financial concepts such as replicating portfolio and arbitrage-enforced pricing do not hold. Secondly, since designers have so many options they can exercise over time, it is not possible with current computing power to solve for comprehensive optimal solutions. Furthermore, it is likely that actual decision-makers would follow their own decision rules, suitable for their time and place. It is therefore necessary to be able to express and replicate this reality in the economic evaluation process.

The approach differs from earlier versions of the systems engineering approach to the analysis of flexibility in that it deconstructs the analysis into its several parts. The idea is to demonstrate the logic of why a flexible approach to design can create value, to show how each of different forms of flexibility add to this value, and to provide reasonable assurance that the recommended design is robust to its assumptions. In short, the approach does more than suggest a design solution and assert its value; the idea is to provide the basis for a convincing argument as to why and how the novel flexible approach to design is appropriate, and thus a coherent rationale for why decision-makers should consider adoption of flexible designs.

The paper demonstrates the approach through the analysis of a case study concerning the development of an LNG plant. Drawing on the then current realities of the situation and the knowledge of our industrial partners, the analysis is realistic for that time and place. It usefully demonstrates how the proposed procedure works. More generally, it indicates how modular design strategies, with the flexibility to deploy capacity over both time and space, have the potential to add significant value. The demonstration thus provides a model for the analysis of LNG and similar production facilities elsewhere.

It is possible to extend the proposed 4-step approach to a range of possible sources of flexible design beyond modularity. The essence of the proposed procedure is indeed to go beyond defining a solution, by creating a logic and an intuitive understanding of the situation, for the purpose of providing persuasive arguments to justify the use of flexible designs as possible improvements over conventional fixed designs based on fixed and generally unrealistic requirements. Follow-on studies on implementation will contribute to further validate the proposed process.

The approach underlines the need for multi-criteria evaluations since no single metric can adequately describe the distribution of performance of any design. Unless a design stochastically dominates all others, decision-makers have to define their preferred solutions by balancing average and possible extreme performances along with other indications of value and cost, such as initial Capex, and situationally appropriate non-financial metrics. In a parallel application for example, Cardin et al. [2013c] evaluated flexibility in emergency services in terms of their expected time responsiveness to incidents over their lifecycle.

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Nomenclature

$a^D, a^U =$ translation parameter in deterministic and stochastic demand models
$\alpha =$ economies of scale factor
$Av =$ annual demand volatility, percent
$b^D, b^U =$ sharpness parameter in deterministic and stochastic demand models
$B =$ slope of learning effect
$C_\alpha^D, C_\alpha^U =$ optimum capacity of a fixed design with economies of scale α, tons per day, deterministic and with uncertainty
$D_0^D, D_0^U =$ LNG demand in years 0, tons per day, deterministic and with uncertainty
$G_t =$ annual LNG demand growth rate
$LR =$ learning rate, percent
$M_T^D, M_T^U =$ forecast limit of demand in year T, tons per day, deterministic and with uncertainty
$r =$ discount rate, percent
$T =$ project lifetime/study period, year
$U_1, U_i =$ Capex required for building the first and the i-th LNG modular plant, \$ million
$V_\alpha^D =$ optimum value of a fixed design under deterministic and economies of scale α, NPV
$V_\alpha^U =$ optimum value of a fixed design under uncertainty and economies of scale α, ENPV
$\Delta_b =$ volatility of sharpness parameter, percent
$\Delta_{D_0}, \Delta_{M_T} =$ volatility of realized demand in percent, in years 0 and T

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