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An Integrated Screening Framework to Analyze Flexibility in Engineering Systems Design

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This paper presents ongoing development for a novel integrated screening framework for flexibility analysis considering multi-domain uncertainty sources and multi-criteria for designing complex engineering systems. The proposed methodology aims to address two main issues in the design process for flexibility: 1) the complexity of exploring exhaustively flexible design strategies under multiple uncertainty sources, and 2) the multiple and possibly conflicting criteria inherent to design decision-making. The proposed screening framework is applied to a real-world capital-intensive project in the oil and gas industry. Current results indicate that the screening model offers better performance than a full exhaustive search of the design space in terms of the number of evaluations and simulation runtime, while providing good design solutions in terms of lifecycle performance. The work provides insights on how to analyze flexibility in the conceptual design of complex systems, especially when computational resources are limited, and design needs to consider multiple decision-making criteria.

1 INTRODUCTION

Designing complex engineering systems is a challenging task. Uncertainty affects systems lifecycle performance, and provides a range of risks and opportunities. For instance in the oil and gas industry, new technologies emerge over time (e.g. Pre-cooled Nitrogen Expander (PreNex) technology for LNG production), customer demand and preferences vary (e.g. fuel type switches from oil to LNG), market prices fluctuate, and local and international regulatory changes (e.g. tax policies for low-carbon technologies, International Maritime Organization (IMO) regulations to prevent pollution from Ships - MARPOL annex VI). Designing complex systems requires considerable capital investments as they are typically large-scale and long-lasting systems. Standard design processes and evaluation approaches, often based on design requirements, optimization, and most likely or average trend forecast (e.g. demand, price) may lead to Lifecycle performance that is not consistent with forecasted trends in the early design phases (Flyvbjerg et al., 2003). New design approaches taking explicit considerations of flexibility and uncertainty are needed to enable a system to better adapt as uncertainty unfolds over time.

Flexibility provides additional value to engineering systems that is typically not recognized from standard design and evaluation procedures. Flexibility is defined here as the "right, but not the obligation, to change a system in the face of uncertainty" (Trigeorgis, 1996). Value improvements ranging between 10% and 30% are observed routinely in many industries, as shown by de Neufville and Scholtes (2011). Flexibility provides a form of insurance against downside potentials. It also positions the system to capitalize on unexpected, upside opportunities. The net effect is typically to increase the overall lifecycle economic performance of the engineering system.

Designing flexible engineering systems is not an easy task. Crucial decisions are needed in the early stages of the design and evaluation process to select and find the best possible alternatives, before detailed design and implementation. The literature in the domain of oil and gas infrastructure shows that high fidelity modeling can often be quite time consuming or even computationally intractable since models take hours if not days to analyze a single design alternative (Güyagüler, 2002, Lin, 2009). Decision makers may not be able to wait until optimization results are ready for design selection under deterministic conditions, let alone consider many uncertainty sources, and flexibility in design strategies. Besides, in the early stages of a project, inputs and models may be uncertain, resulting in a high-fidelity model that does not necessarily give better results than a mid-fidelity one (Lin, 2009). In addition, the best flexible design alternatives need to satisfy many criteria, and possibly conflicting goals. For instance, the aim might be to choose a design based on the highest expected performance value (e.g. expected Net Present Value or ENPV), 5th (P5) and/or 95th (P95) values, volatility of performance outcomes, and initial capital expenditure (CAPEX).

This paper presents ongoing development of a novel screening framework that addresses the issue of computational complexity in flexibility analysis, in addition to multi-domain uncertainty, and multi-criteria analysis. The Related Work section presents the background motivating this study. The Methodology section describes the proposed screening framework to evaluate the baseline design alternatives and flexible designs. The Application section demonstrates a case study along with current results for the proposed framework in an oil and gas project. The Discussion and Conclusion sections provide practical insights to practitioners, discusses limitations, and directions for future work.

2 RELATED WORK

Four main axes of research opportunities are related to this work: 1) design for flexibility, 2) multi-domain uncertainty, 3) screening model, and 4) multi-criteria decision-making. The following accounts for the main contributions motivating this work, and the corresponding research gaps.

Yang (2009) proposed a screening model to explore planning decision considering demand uncertainty in the auto industry manufacturing systems. Her framework was developed to make decisions in three domains of strategic, tactical and operation, aiming at finding promising flexible strategies efficiently. There are, however, some limitations concerned with this study. For problem modeling, only design variables were considered for optimization in the flexible system configuration, and no decision rules[1]

[1] A decision rule is a triggering mechanism determining when it is appropriate to exercise a particular flexibility, based on some uncertainty observable. For instance, one may decide to expand LNG production capacity after demand reaches a certain threshold. Decision rules can be modeled to assess the value of flexibility.

were used to adapt the configuration of the system under demand uncertainty. As a result, tactical level flexibility strategies were ignored, such as the ability to expand production capacity in each plant. The study only considered one uncertainty source (i.e. product demand), while many others exist (e.g. material price).

Lin (2009) proposed a four-step screening model to identify and evaluate architecture and developing strategies for capital intensive projects in the early stages of the design. Unlike Yang's research (2009), Lin benefited from decision rules to embed the flexibility in the system. On the other hand, the procedure used to tuning the decision rules was based on engineering practices and a trial-and-error approach, which needs iterative procedure which leads to bios sampling in design space. There is a need for a more systematic search process to evaluate flexibility decision rules, which are crucial to generate value enhancing solutions.

Gupta and Grossmann (2012) presented a mixed integer nonlinear programming model (MINLP) for offshore oilfield development problem. The proposed model considers multisite investment and operation planning decisions considering three main components of oil, water, and gas, aiming at maximizing total NPV for long-term planning horizon. The model involves decisions related to floating production, storage, and offloading (FPSO) installation and expansions, field−FPSO connections, well drilling, and production rates in each time period. All decisions, however, were made based upon deterministic conditions, which may not be appropriate for flexibility analysis. Furthermore, considering a single fiscal objective may not satisfy the stakeholder's preferences.

Ross (2003) introduced a structured framework for designing complex engineering systems considering multi-attribute decision making concept. The Multi-Attribute Tradespace Exploration (MATE) framework relies on a tradespace spanned by completely enumerated design variables. The full enumeration of a tradespace can be computationally demanding. Hence, this presents a research opportunity to explore such a vast solution space more efficiently by minimizing the computational time through removing sampling bias in tradespace enumeration.

Güyagüler (2002) introduced a hybrid optimization technique (HGA), based on genetic algorithms (GA) combined with Kriging techniques to determine the best location for new wells in offshore petroleum industries. There are limitations concerned with problem modeling, and the fact that only well placement uncertainties were addressed. Other sources of uncertainty can be considered at operational, tactical, and strategic levels to deliver more valuable design alternatives.

Tavakkoli-Moghaddam et al. (2012) developed a multi-criteria model for operational planning of cellular manufacturing systems considering alternative process routs. A meta-heuristic algorithm was proposed to tackle the computational burden of the branch and bound algorithm. The main issue with the work is that all parameters considered are deterministic, which is not appropriate for flexibility analysis.

2.1 Main contributions

The main contribution of this ongoing research is to introduce an integrated multi-criteria screening framework to explore flexible design strategies efficiently and effectively. None of the work above considers the following four aspects simultaneously: 1) flexibility analysis for design decision-making under uncertainty, 2) a screening approach alleviating the complexity of real-world computationally intensive simulations, 3) a multi-criteria search approach to bring flexible designs consistent with stakeholders' preferences, and 4) multi-domain uncertainty to deliver better value-driven designs via explicit considerations of operational, tactical, and strategic sources of flexibility.

3 METHODOLOGY

A structured methodology is developed to address the following research questions: 1) how can one find the best flexible design alternative with less computational effort compared to full exhaustive search, considering multiple decision-making criteria, and multi-domain uncertainty sources?, and 2) with regards to the case study, what should be the best flexible design and deployment strategy in the face of uncertain market demand? The above questions are addressed by first proposing a novel screening framework accounting for the four axes mentioned above. The proposed framework is then used to analyze a LNG production system as a demonstration case study. The goal is to quantify potential value improvements not recognized by standard design and evaluation approaches, while trading off efficient design space exploration to find the best flexible design and management strategies for this system

3.1 Proposed Screening Framework

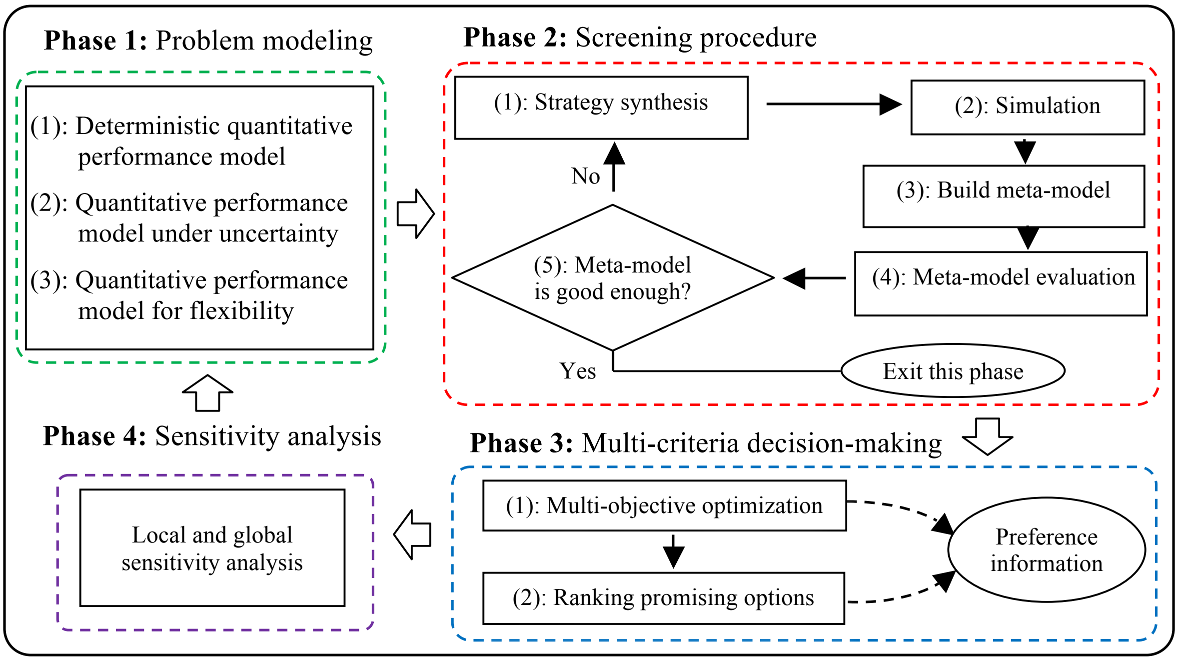


Figure 1: Proposed multi-criteria screening method for flexibility

3.1.1 Phase 1: Problem modeling

Problem modeling is the starting phase of the framework, and includes three steps (see):

Step 1: Baseline Quantitative Performance Model

This step generates a baseline quantitative performance model to evaluate the design alternatives subject to a number of assumptions, such as market parameters, design parameters, cost and revenue drivers. A performance-based model is developed, and lifecycle performance of different design alternatives is measured using different metrics (e.g. Net Present Value or NPV). The initial model is based on deterministic values for the uncertainty factors, and fixed design variables and parameters.

Step 2: Uncertainty Analysis

In step 2, the lifecycle performances of the designs are investigated under uncertainty of the major uncertainty drivers. The lifecycle performance of the system is recognized as highly sensitive to varying sources of uncertainty. To model the behavior of uncertainty throughout the evaluation period, a stochastic function can be used such as Geometric Brownian Motion (GBM), S-curve function, Mean Reverting Process, etc. Using this stochastic model and Monte Carlo simulation, one can generate a large number of possible scenarios (e.g. LNG demand). After the risk profiles of the different design alternatives are generated, they can be compared based on different performance metrics (e.g. average or mean value, value at risk captured as 5^{th} performance percentile, variability).

Step 3: Flexibility Analysis

Step 3 introduces the notion of flexibility in the design, deployment, and evaluation of the different alternatives. Flexible design opportunities are considered to cope with the major uncertainty drivers based on a number of generic real option strategies (e.g. capacity expansion/reduction, switching inputs/outputs, deferring investment, etc.) (Trigeorgis, 1996). Flexible strategies are characterized by a combination of design variables and decision rules, thereby defining the design space. Decision rules are embedded in the evaluation model using logical statements such as “IF…, THEN, ELSE, …”.

3.1.2 Phase 2: Screening procedure

The screening procedure benefits from the response surface approach, through building a meta-model. The aim is to reduce the computational burden of evaluation process required using the original simulation model. To capture the nonlinearity of the system response (e.g. value of flexibility or ENPV), a DACE (Design and Analysis of Computer Experiments) model is applied. The key to using response surfaces for finding the best flexible design lies in balancing the need to exploit the approximating surface (by sampling where it is optimized) with the need to improve the approximation (by sampling where prediction error may be high). Finally, this phase terminates via a credible stopping criterion, as shown in Figure 1.

3.1.3 Phase 3: Multi-criteria decision-making

The dominant distinct candidate flexible designs are generated based on generalized goals and domain-specific preferences. Exploring the solution space based on generalized preferences as primary goals can be done using an evolutionary multi-objective search engine to find the Pareto front solutions. The following tasks are considered: 1) using finalized meta-model as a surrogate of simulation model, 2) finding promising dominant flexible configurations, and 3) clustering distinct dominant design through identifying the region of interest on Pareto front. In 2), distinct candidate flexible designs are ranked based on qualitative preference such as sustainability, safety, durability, reparability, maintainability, manufacturability, and modularity among others (Allen et al., 2002). The following tasks are then considered: 1) multi-attribute decision-making, and 2) weighing of the different criteria based on decision-makers' preferences.

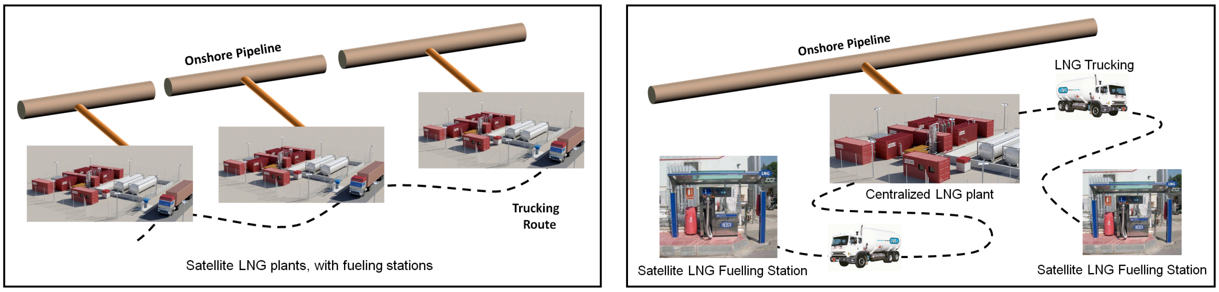
3.1.4 Phase 4: Sensitivity analysis

In order to observe how sensitive the model is subject to some critical parameters, several local and global sensitivity analyses are conducted. This analysis may seek different purpose such as the effect of having flexibility in different domains of study, different decision rule parameters, a range of design parameters, etc. The results of this analysis can be used to see that the best flexible designs proposed by the framework if remain unchanged.

4 APPLICATION

4.1 Case study

The problem is to design a LNG production and fueling system for trucks used in on-road transportation and mining operations. There are currently two design alternatives considered (see Figure 2): 1) deploying small decentralized LNG production facilities combined with fueling stations, or 2) a big centralized production facility with satellite fueling stations along the pipeline.



(a) (b)

Figure 2: Decentralized (a) and centralized (b) design alternatives

Design alternative 1 – referred as decentralized system in Figure 2 (a) – consists of 5 satellite plants with 20% production capacity of the centralized plant at each site, along with fuelling stations along the pipeline at strategic points to accommodate demand. Design alternative 2 – referred as centralized strategy in Figure 2 (b) – consists of building a centralized LNG plant with 100% capacity equipped trucking fleets for distributing the fuel to satellite fueling stations. For design alternative 2, fueling stations should be laid out along the trucking routes.

A third design alternative is considered to introduce the notion of flexibility, which is described as on-site capacity expansion. This strategy is the most relevant to deal with uncertain localized demand growth, a major uncertainty driver to economic performance. This flexible decentralized solution is a flexible version of design alternative 1. It consists of 5 satellite plants deployed first with 10% initial capacity. Then, depending how fast the demand grows over time, their capacity can be expanded to a maximum of 20% capacity, only when required by localized demand. This design alternative contrasts with alternatives 1 and 2, which are both rigid inflexible design and deployment strategies.

4.2 Analysis using proposed methodology

4.2.1 Phase 1: Problem modeling

Step 1: Baseline DCF Model

The performance metric used in this example is NPV, calculated as the sum of discounted cash flows throughout the project lifecycle T = 20 years – see equation (1). Variables TR_t and TC_t show the total revenues and costs incurred in years t = 1, 2, ... T, and r is the discount rate with $0 \leq r \leq 1$.

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

Step 2: Uncertainty Analysis

A stochastic S-curve function is assumed to simulate LNG demand over the study period, shown in equation (4). The rationale is that demand for LNG initially grows slowly for some time, because the market and LNG infrastructures are evolving. Then over time demand increases exponentially, and finally tapers as it approaches a saturation limit. Variable M_l is the maximum expected demand for LNG at demand point l; b is the sharpness parameter that determines how fast demand grows through the temporal range to reach the upper bound for demand at any demand point l, M_l; a is a translation parameter that interacts with b, but translates the curve horizontally. Since economic performance is highly influenced by the sharpness parameter b, uncertainty is considered and modeled using an additional uncertainty factor σ_b. Monte Carlo simulation is used to simulate a wide range of scenarios.

$$LNGD_{lt} = \frac{M_l}{1 + ae^{-b(1\pm\sigma_b)t}} \tag{2}$$

Step 3: Flexibility Analysis

To embed the capacity expansion policy, a simple decision rule was incorporated in the Excel® DCF model: IF "*observed demand in the last year was higher than a certain threshold value at a given site*" THEN "*expand capacity to its maximum planned level until the end of the lifecycle"* ELSE *"do nothing*". The threshold value corresponds to the maximum capacity that can be reached at each site, which is 20% of total production capacity of the centralized plant. For example, decision-makers may decide to add another plant as soon as demand reaches 75% of maximum planned capacity for the site.

Figure 3 shows the simulation results corresponding to all design alternatives, with the decision rule affecting only the flexible decentralized design. The vertical dashed lines represent the ENPV over 2,000 simulations for the three design alternatives. For the inflexible decentralized design alternative 1 (blue) ENPV = \$10.23 million, for the centralized design 2 (red) ENPV = \$13.6 million, and for the flexible decentralized design alternative 3 (green) ENPV = \$18.45 million. For the flexible case, the following decision rule was used: if "*observed demand in the last year was higher than 85% of maximum planned capacity at the site (i.e. 85% of 20% of total capacity)*" then "*add 10% capacity in extra LNG production capacity*" else "*do nothing*". Note that the decision rule is applied independently at each of the five sites, depending on the demand scenario realized. It can be applied only once in any year t. Once full capacity is reached, it remains at that production level.

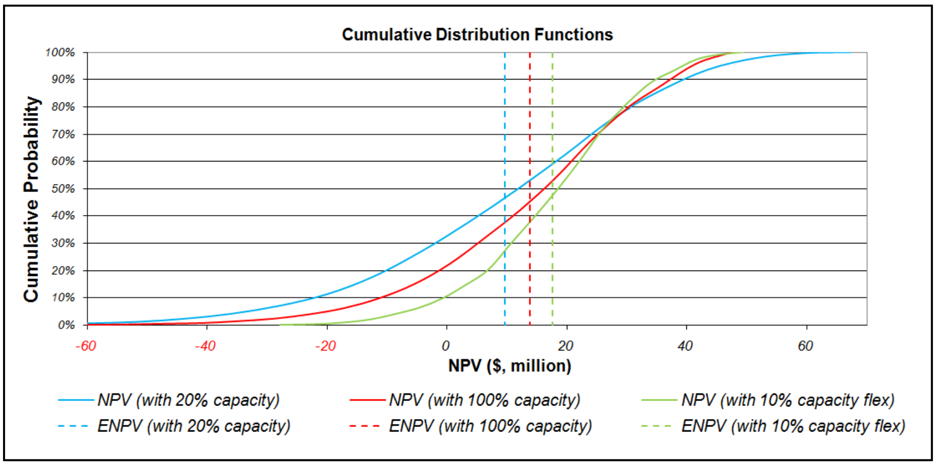


Figure 3: Cumulative distribution of NPV based on 2,000 LNG demand scenarios

The value of flexibility is calculated as shown in equation (3):

$$\text{Flexibility Value} = \text{ENPV}_{\text{flexible design}} - \text{ENPV}_{\text{inflexible design}} \tag{3}$$

Here the baseline design is the inflexible centralized design 2. The results in Figure 3 show that the value of flexibility is about \$18.45 million – \$13.60 million = \$4.85 million. This expected value can be compared with the cost incurred to enable the flexibility (e.g. buying extra piece of land, preparing existing infrastructures at production site for possible expansion, etc.). This provides a way to make a better informed decision in flexibility, and determine whether it is worth the extra cost.

4.2.2 Phase 2: Screening procedure

In this phase the proposed methodology benefits from statistical meta-modeling rather than traditional design of experiment, as used in (Lin, 2009, Yang, 2009). In the literature on mathematical geology, the approach was called 'Kriging', and dates back to the early 1960s (Krige, 1960). In the original method, the data consisted of core samples taken from different locations, and the goal was to find a function that approximates the underground concentration of a valuable mineral. More recently, the Efficient Global Optimization (EGO) proposed by Jones et al. (1998) is a Kriging meta-model based optimization method developed from Bayesian based optimization methods. The sequential Kriging meta-model is used to create an adaptive response surface. The Kriging mata-model is chosen for the screening framework because it:

1. Effectively balances the local (also refereed as exploitation) and global (also refereed as exploration) search strategies to explore the solution space efficiently and systematically, while the traditional RSM methods (e.g. quadratic regression models) have some limitations as indicated by Jones et al. (1998).
2. Benefits from adaptive sequential response surface procedure, which is based on a Gaussian process, to lessen the computation time and evaluation number, as can be seen in the results.
3. Takes advantage of a viable stopping criterion which is tied with simulation-optimization procedure to control balancing between exploration and exploitation.
4. Is easy to implement, especially when Excel$^{(R)}$ and Matlab$^{(R)}$ are properly interfaced.

Equation (4) calculates the expected improvement of current response surface (Jones et al., 1998). Where, Φ is the cumulative normal distribution and ϕ is the normal distribution; f_{min} shows the minimum value among the tried points, where $f_{min} = \min(y^1, \dots, y^n)$; $\hat{y}$ is DACE predictor; s shows the standard error/mean square error of the Kriging meta-model. Once the expected improvement gives a better value, the optimum point X is obtained to run simulation for this point.

$$E[I(X)] = (f_{\min} - \hat{y})\Phi\left(\frac{f_{min} - \hat{y}}{s}\right) + s\phi\left(\frac{f_{min} - \hat{y}}{s}\right) \tag{4}$$

The following Kriging technique is applied to create an adaptive response surface (also see Figure 1):

- step 1 and 2): Conduct initial design of experiment (i.e. "space-filling" using Latin Hypercube sampling) and conduct initial simulation (e.g. Monte Carlo Simulation)
- step 3): Fit the parameters of a DACE model using maximum likelihood estimation.
- Once the initial DACE surface is fit and any transformation made, the iterative procedure starts.
- step 4): The expected improvement function is maximized using MATLAB function called "fmincon"
- Step 5): If the maximum value of the expected improvement (EI) function is less than the EI threshold value then
  a. Step 5,Yes): Global search is 'expected we stop. Otherwise
  b. Step 5, No): Sampling of the design space including design variables and decision rules is conducted where expected improvement is maximized, re-estimate the DACE parameters
- Iterate until stopping criteria at step 5 is met.

Exploring the flexible design strategies exhaustively is a computationally intensive task. Therefore, the proposed screening procedure based on Kriging meta-modelling is applied to reduce the computational burden. It is used as demonstration to find the optimal capacity expansion decision rule by efficiently exploring the flexible design space instead of a full exhaustive search. While the threshold value is a continuous function varying between 1-100%, the screening approach only samples a few points in this simplified design space. While this analysis is shown as an example, it can be extended to analyze a combination of other decision rules and physical design variables (e.g. initial capacity).

To show that the simulation-optimization procedure is valid within an acceptable flexibility value gap, 7 computer experiments were conducted using different parameters. Due to space limitation, Table 1 shows comparison between exhaustive search and screening model in terms of the best threshold values found and the values of flexibility for the first three. The same number 2,000 demand scenarios were used for both screening and exhaustive search in each replication.

The value of flexibility obtained by exhaustive search is higher than the one found by screening model. The flexibility value gaps are illustrated in the last column. Table 2 shows comparisons between exhaustive search and the screening model in terms of the number of evaluations (i.e. simulations in untried points) required. Table 3 shows a comparison in terms of computational runtime on a Windows 7 platform with 8 GB RAM and 3.3 GHz processing speed.

Table 1: comparison between exhaustive search and screening model in terms of threshold value and flexibility value (FV)

No.	Simulation Replication Number	Exhaustive Optimum Threshold Value	Screening Optimum Threshold Value	Exhaustive Optimum FV	Screening Optimum FV	$\left(\frac{FV_{Exhaustive} - FV_{screening}}{FV_{Exhaustive}}\right) \times 100$
1	15	0.72	0.71	4.95	4.63	6.46%
2	1	0.71	0.74	5.23	5.08	2.89%
3	3	0.73	0.75	5.29	5.13	3.02%

Current results suggest considerable improvement compared to a full exhaustive search both in terms of the number of evaluations required, and simulation runtime. Both tables also show that further improvement occurs when the number of replications is bigger.

Table 2: comparison between exhaustive search and screening model in terms of the number of evaluations required

No.	Simulation Replication Number	Exhaustive Number of Evaluations	Screening Number of Evaluations	Improvement for Number of Evaluations
1	15	46	5	89.13%
2	1	46	9	80.43%
3	3	46	5	89.13%

Table 3: comparison between exhaustive search and screening model for computational runtime

No.	Simulation Replication Number	Exhaustive Runtime (sec.)	Screening Runtime (sec.)	Runtime Improvement (sec.)
1	15	≈ 10,350	1,358.49	86.87%
2	1	≈ 690	207.68	69.90%
3	3	≈ 2,070	294.11	85.79%

4.2.3 Phase 3: Multi-criteria decision-making

The best design alternative can be chosen based on many criteria, such as those shown in Table 4. All values for the flexible systems correspond to the best decision rule as found through optimization, using the screening technique (i.e. threshold value 72% of maximum planned capacity). The aim is to choose a design based on the highest value for ENPV (or mean NPV), P5 (5^{th} percentile of NPV distribution, giving a sense of the downside potentials, or Value At Risk) and P95 (95^{th} percentile, giving a sense of the Value at Gain), and smaller values for standard deviation, and initial CAPEX.

Results in Table 5 show that the flexible design would be best among all decision criteria, except for P95. The reason is that if high demand growth scenarios occur, the decentralized plant is better positioned since it has more capacity installed early on. The flexible system, however, provides better economic performance on average (i.e. mean NPV), better protection against downsides (i.e. P5) as would insurance do, less variability (i.e. standard deviation), and requires less initial CAPEX.

Table 4: Summary table of multi-attribute decision-making[1]

Metric	Centralized Design Under uncertainty	Decentralized Design Under uncertainty	Flexible Design	Best Design?	Flexibility Value (Improvement) [2]
Initial capacity (tpd [3])	100%	(5×20%)	(5×10%)	N/A	N/A
Mean NPV	45.69%	0%	**100%**	Flexible	35.66%
P5	41.56%	0%	**100%**	Flexible	70.96%
P95	5.72%	**100%**	0%	Decentralized	0.00%
Standard deviation	47.82%	100%	**0%**	Flexible	23.00%
Initial CAPEX	48.73%	100%	**0%**	Flexible	19.02%

[1] All figures were normalized between 0% and 100% to mask the confidential data

[2] Flexible design compared to the centralized design in terms of given criteria – calculated based on the original data; [3] Ton per day

All design alternatives are analyzed based on different criteria, aiming at finding dominant design alternative(s). To do so, RR-Pareto technique developed by Raphael (2011) was used and all criteria were considered as objective functions. Essentially, this technique benefits from Pareto dominance concept and a practical interactive feature so that designers' preferences can be considered quantitatively. This multi-criteria technique shows that the flexible design is the dominant design alternative using RR-PARETO3 filtering, as shown in Figure 4.

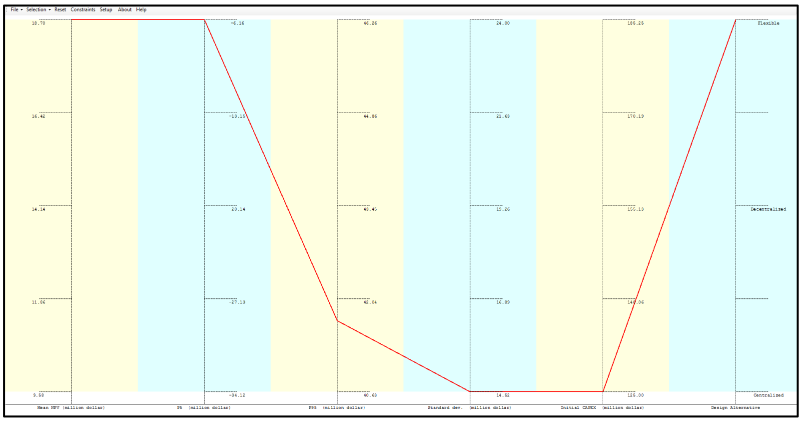


Figure 4: Parallel axis plot of dominant design alternatives based on RR-PARETO3 filtering - Source: (Raphael, 2011)

4.2.4 Phase 4: Sensitivity analysis

The sensitivity analysis was conducted in terms of different volatility of sharpness parameter and the discount rate. Results indicate that the more volatile LNG demand is, the higher the value of flexibility. This confirms the fact that flexibility is more valuable the more uncertainty there is. At higher discount rates, there are more incentives to defer additional capacity deployment, which is translated here by the higher value of flexibility. For brevity, the results are not presented in this paper.

5 DISCUSSION AND CONCLUSION

This research proposes a screening framework to efficiently explore the solution space of flexible design and management strategies in complex engineering systems. The proposed framework was applied to a demonstration analysis of a real-world oil and gas system. Current results demonstrate promising improvement on economic lifecycle performance by exploiting ideas of flexibility in comparison to a baseline design concept developed from standard design and evaluation approaches. Observations on a simplified case show that the screening model offers better performance than a full exhaustive search of the design space in terms of the number of evaluations required and of the simulation runtime, while providing a good flexible design solution in terms of lifecycle performance. Using this approach, decision-makers and practitioners can explore flexible design strategies at a fraction of the computational cost, while finding good enough solutions as compared to a full exhaustive search that may require hours if not days of computations on standard computers.

5.1 Limitations

In the proposed methodology, a Kriging meta-model was used as surrogate model to reduce the computational complexity of the screening process. Therefore validation and verification of the meta-model requires further investigation since it is used as the basis for the following decision-making phase. The proposed framework as a generalized method can be applied for a wide range of problems in engineering systems, although applications are needed for full validation. Also, the underlying assumption is that designers of engineering systems have knowledge about different sources of uncertainty and flexibility based on their expertise and experiences. It is also assumed that the decision makers are clear about their generalized goals and domain-specific preferences. In reality, however, these assumptions may not be as clear. Some mechanisms have been developed to help designers generate flexible design concepts (e.g. (Cardin et al., 2012)) and determine salient utility measures (e.g. Ross, 2006) and help alleviate these concerns, to be used in combination with the proposed screening framework.

5.2 Future work

This paper presented an ongoing research regarding a multi-criteria screening framework for flexibility analysis considering multi-domain uncertainty. While the methodology was applied to a simplified real-world problem, the framework needs to be developed so that it can be applied for large-sized real-world problems. This involves extending the multi-criteria part of the analysis, considering more decision rules and design variables, and extending to consider more than one uncertainty sources (i.e. here only demand was considered) and flexibility strategies (i.e. here only one strategy was analyzed).

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